UTILIZING DATA-DRIVEN APPROACHES
TO EVALUATE AND DEVELOP
AIR TRAFFIC CONTROLLER ACTION PREDICTION MODELS

A Dissertation

Submitted to the Faculty

of

Purdue University

by

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In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

August 2020

Purdue University

West Lafayette, Indiana

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ACKNOWLEDGMENTS

Advice given by Dr. Steven J. Landry and the committee members (Dr. Karen Marais, Dr. Roshanak Nateghi, and Dr. Denny Yu) have been a great help in this work.

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ABSTRACT

Boo, Jeongjoon Ph.D., Purdue University, August 2020. Utilizing Data-Driven Approachesto Evaluate and DevelopAir Traffic Controller Action Prediction Models. Major Professor: Steven J. Landry.

Air traffic controllers (ATCos) monitor flight operations and resolve predicted aircraft conflicts to ensure safe flights, making them one of the essential human operators in air traffic control systems. Researchers have been studying ATCos with human subjective approaches to understand their tasks and air traffic managing processes. As a result, models were developed to predict ATCo actions. However, there is a gap between our knowledge and the real-world. The developed models have never been validated against the real-world, which creates uncertainties in our understanding of how ATCos detect and resolve predicted aircraft conflicts. Moreover, we do not know how information from air traffic control systems affects their actions. This Ph.D. dissertation work introduces methods to evaluate existing ATCo action prediction models. It develops a prediction model based on flight contextual information (information describing flight operations) to explain the relationship between ATCo actions and information. Unlike conventional approaches, this work takes data-driven approaches that collect large-scale flight tracking data. From the collected real-world data, ATCo actions and corresponding predicted aircraft conflicts were identified by developed algorithms. Comparison methods were developed to measure both qualitative and quantitative differences between solutions from the existing prediction models and ATCo actions on the same aircraft conflicts. The collected data is further utilized to develop an ATCo action prediction model. A hierarchical structure found from analyzing the collected ATCo actions was applied to build a structure for the model. The flight contextual information generated from the collected data was used to predict the actions. Results from this work found that the collected ATCo actions do not show any preferences on the methods to resolve aircraft conflicts. Results found that the evaluated existing prediction model does not reflect the real-world. Also, a large portion of the real conflicts was to be solved by the model both physically and operationally. Lastly, the developed prediction model showed a clear relationship between ATCo actions and applied flight contextual information. These results suggest the following takeaways. First, human actions can be identified from closed-loop data. It could be an alternative approach to collect human subjective data. Second, the importance of evaluating models before implications. Third, potentials to utilize the flight contextual information to conduct high-end prediction models.

1. INTRODUCTION

Ensuring safe flights by controlling air traffic is the primary reason for having air traffic controllers (ATCos) to supervise aircraft activities just as equivalent to having traffic lights and signs on the road. However, we do not know how ATCos are "actually" manage aircraft conflicts that were predicted during air traffic control operations in real-time. Many aspects of ATCos were studied for a long time by many researchers in various perspectives and directions. However, the reason for claiming such a statement is in the characteristics of those conventional studies about ATCos actions for resolving predicted aircraft conflicts.

Air traffic control systems are critical to safe flight operations, and tasks of ATCos take a significant portion of it. One of their primary tasks to ensuring safe flights is detecting possible aircraft conflicts that either violate the rule of separation between aircraft or predicted to cause a collision. Another one is resolving the predicted conflicts by making aircraft to alter them from original flight trajectories. An aircraft conflict resolution can be achieved by changing flight path, altitude, speed, or applying two or more of these methods together. These two tasks are called conflict detection and resolution (CD&R), and researchers focused on understanding these two tasks to use such knowledge to improve air traffic control systems. However, results from these studies do not represent ATCo actions. These studies are based on human subjective approaches. They are direct and effective ways to study human subjects. However, this type of approach has an issue regarding generalization. To generalize a result from a study, it requires a reasonable number of samples considering the target's total population. Human subjective studies require the sampling of participants. Recruiting participants on any experiment is not an easy task, and targeting a specific group of people is more challenging. ATCo is not a common type of job. It is impractical to recruit a statistically reasonable number of ATCo to a study. Therefore, the results of the study have to confront generalization issues. Their designs or experiments also affect knowledge about the ATCos. These human subjective studies were taken place in experiments with simulated environments and scenarios designed and developed by researchers, not the ATCos. Moreover, regardless of the fidelity of a simulation, it is distanced from the real-world. Laboratory works are often tested outside to address the discussed issues. However, the studies on ATCos never been validated against actual controller actions in the real world. Along with safety issues on flight operations, researchers did not have a proper method back then.

Knowledge about ATCo actions on CD&R can be implemented to improve air traffic control systems. One way of the development is in automating the current tasks of ATCo to reduce human errors. At the same time, researchers and stakeholders aim to build an automated system to perform like ATCos. However, the results of the conventional studies have limitations in satisfying this condition. Recent technological advances and changes in policies allowed a different approach to the study. This work introduces a method contributing to our knowledge about ATCo actions on aircraft conflict resolution. The approaches utilize a large scale of real-world flight data that reflects actual ATCo actions. With such information, this work proposes a method to evaluate existing aircraft conflict resolution models against actual ATCo actions. Also, it implements contextual information regarding the actions to develop a model to predict ATCo actions on predicted aircraft conflicts.

This work includes a series of three parts: collecting necessary information, evaluating the models, and developing a model. Frist part identifies predicted aircraft conflicts and accompanying actual ATCo actions from flight data. The second part takes this information to evaluate the conflict resolution performance of existing models against ATCos. The third study uses the results of the first part to conduct a prediction model.

The first part of this work is about collecting actual ATCo actions. Collecting real-world data is the fundamental part of this work to proceed evaluation of existing aircraft conflict resolution models and conducting a prediction model based on actual ATCo actions. This part collects the actions from flight tracking data, which collected for a period. A set of algorithms was developed to extract ATCo actions from the data since it just presents how an aircraft flew and planned to operate. The algorithms assume an ATCo alters an aircraft from its planned route, only when it is necessary. Furthermore, one of the conditions that satisfy it is when an aircraft conflict is predicted. Developed algorithms search two specific situations from the collected flight data. First, they look for a deviation from a planned route by comparing it against the flown trajectories of an aircraft. Then it searches the existence of another aircraft that is expected to cause a conflict with the first aircraft if it was flying as planned. Results of these algorithms provide a pair of aircraft that was expected to cause a conflict and ATCo altered their operations. Eventually, how an aircraft deviated shows what kind of ATCo action was taken to resolve a conflict.

The second part of this work introduces a method to evaluate existing aircraft conflict resolution models against actual ATCo actions. As stated above, the conventional studies on ATCo actions never been validated against actual ATCo actions. This part of the study proposes a method to evaluate such models with the ATCo actions collected from the first part. The proposed method consists of three measurements to answer the following questions to evaluate an existing model from various perspectives. First, does a solution generated by a prediction model is different from a corresponding ATCo action? If they are different, what makes them different? Also, can we apply the model solution to an aircraft conflict instead of applied ATCo action? The first measurement qualitatively compares an ATCo action on a collected conflict against model solution generated by inputting a conflict case to an existing model. The second measurement investigates results from the first measurement to identify differences between an ATCo action and a model solution on the corresponding conflict. Then it finds explanations on the identified information. The last measurement checks whether a model solution is plausible on the cases where a model solution and its counterpart are resulted as different from the first measurement.

The third part of this work develops a prediction model based on the collected ATCo actions. The discussed conventional studies focused on studying the relationship between an aircraft conflict and how ATCo resolve it to come up with the resolution models. Instead of investigating the relationship, the developed model looks into a statistical relationship between ATCo actions and contextual information that represents predicted aircraft conflicts. The developed model depicts the structure of ATCo actions. It contains sub-models that are hierarchically connected to each other. Each sub-model makes one decision, and the following sub-model makes another decision to fill the detail of an ATCo action. These decisions include a selection of an aircraft to deviate, which type of maneuver to apply, and how to apply the selected maneuver.

As a result, this work introduces a method to collect actual ATCo actions. Then it utilizes the information to evaluate existing aircraft conflict, resolution models. By conducting a model based on the collected information, this work eventually compares the performance of two different types of models to present strengths and limitations coming from differences in conducted approaches. Additionally, the result contributes to our knowledge about understanding ATCo more accurately for improving air traffic control systems.

This document includes five main sections besides the Abstract and Introduction in the main content. The following section is the Background to provide readers the necessary information to support methods used in each part of this work. After the Background, methodologies, and results of each part of this work are presented in order. Lastly, takeaways of this work are discussed to summarize findings from each part and as an overall. After the main sections, the Appendix lists additional details of this work of the previous sections.

2. BACKGROUND

The first form of air traffic control system was flagging aircraft to signal whether they are clear to land or need to wait at Lambert Field by Archie W. League in 1929 [1]. In 1930, Cleveland Hopkins International Airport launched a milestone of current airport traffic control by constructing a control tower with radio devices for communication purposes. Along with the control systems at airports, en-routing (mid-air) traffic control started with a method called "paper strip" [2]. At that time, the controllers did not have technologies and infrastructures to monitor and communicate with en-routing aircraft. Thus, they had to assume aircraft are following their original route and estimate their progress or adjust the pace by getting reports from pilots while communications were possible with ground stations. This manual method was possible at that time because there was not much traffic as nowadays, and they were not as fast as jets.

The current system is not fundamentally different from the paper strip method, except now we can track and communicate with aircraft in real time. The paper strip method utilized a physical map to indicate locations of aircraft, but the current traffic control system uses displays to show them automatically. Also, three different types of radars transit signals with flights and their frequencies become higher, and coverages become shorter as aircraft approach to airports and vice versa. An ATCo manages an airspace sector, and there are multiple sectors in one airspace (currently, the U.S. has 22 airspaces). We define a pair of aircraft conflicts when they are expected to invade each other's zone which is called the protected airsapce zone. In the U.S, each en-routing aircraft in high altitude has the standardized zone that other aircraft are not recommended to enter. Researchers describe this zone as a flat and vertical cylinder around an airplane, which is 5 nautical miles wide horizontally and 1000 feet tall vertically.

FAA provides a guideline to train ATCos to resolve aircraft conflicts [3]. However, details in training may differ by instructors and trainees. Also, individual ATCos use different methods to resolve conflicts based on their experience or characteristics. Moreover, there is little information about ATCo actions. There are three methods to collect ATCo actions: 1) finding ATCo controls from communication with pilots, 2) conducting human subjective experiments, and 3) utilizing air traffic data. ATCos communicate with pilots to deliver various information, including controls, to alter the current routes as regulated by the Federal Aviation Administration (FAA) [4]. Researchers use the last two methods more frequently than the first one due to difficulties in accessing the information. There are two practical ways to obtain communications. The first one is obtaining information recorded by aircraft. There are FAA advisory circulars and international standards for recording the communication from aircraft [5–7]. On the other hand, there are studies to focus on studying the actions of the pilots [8, 9]. The second one is using the communications captured by a third-party personnel. The strength of this method is in collecting specific ATCo actions. However, not all communications are public, and some records may not exist. Also, the recordings include many different conversations, which make it difficult to locate the desired conversation from the records.

Researchers studying tasks of ATCo are taking qualitative and quantitative approaches to explain and model them. Qualitative studies focused on understanding the cognitive elements of ATCo actions for the tasks by directly observing samples of ATCos. For example, Wickens, 1984 applied methods of psychology to understand how human operators perform tasks cognitively [10]. Other qualitative researches introduced the situation awareness and mental model [11–13]. Sarter and Woods, 1991 suggested a relationship among findings of human subjective studies [11], and Niessen et al., 1998 introduced a complete form of the ATCo mental model [14]. Meanwhile, aviation organizations such as FAA, NASA, and Eurocontrol were interested in external ones. They observed and interviewed ATCos to identify and list ATCo strategies on performing the CD&R [15–17]. Studies integrated individually collected behaviors to form prescribed models. Quantitative approaches viewed the CD&R as a geometry problem and applied optimization perspective to minimize various operational costs. Tomlin, Pappas, and Sastry, 1998 introduced an optimization model that can provide horizontal resolutions [18]. Other quantitative methods utilize stochastic approaches and force field modeling methods, but they may not resolve a conflict. The most advanced approach so far is combining both prescribed and mathematical models. The Auto Resolver is one of the most advanced models. It utilizes a prescribed method to prioritize which mathematical model to provide solutions [19].

Most human subjective models of the CD&R are unable to measure their performance quantitatively due to their qualitative and macroscopic descriptions. Prescribed models could check their conflict resolution performance, but they were utilized for other purposes. Borst et al., 2016 tested whether the "best practice" strategies to novice ATCo affect their performance [20]. The study measured human performance under two different criteria: correctness of the CD&R and related response time. Optimization models such as Bilimoria, 2000 tested their model with a set of scenarios that has only two aircraft to check if the models can function adequately [21]. Some studies tested their models with flight data under limited circumstances. Granger, Durand, and Alliot, 2001 applied their algorithm into a flight simulator to measure detection and resolution ratio with related time cost [22]. NASA conducted a series of studies to adopt automated CD&R [23–25]. The studies measured the performance of the models regarding response time and accuracy, and their primary purpose was to see if ATCos can adequately operate the automation.

The human subjective studies indicated that perceived information plays a critical role in ATCo tasks. Starting with Leplat and Bisseret, 1966, many studies identified factors influencing the tasks [26]. However, their identification was not the primary purpose of studies. FAA's report, on the concept of ATCo, lists explicit information that ATCos utilize to perform their tasks [27]. Studies like Chatterji and Sridhar, 2001 measured the workload of ATCo based on perceived information (e.g., the number of aircraft at the moment) [28]. Also, Wickens et al., 1997 lists information in each part of the proposed model of the human subjective process [29]. Significant points from these studies are proposing the existence of a pool of information, and ATCos prioritize or select a specific set for their decision-making processes. Unlike these studies, most mathematical models only adopt geometric information such as coordination of aircraft and its vector on their algorithms.

The majority of previous studies researching CD&R of ATCos took human subjective approaches to collect the information. In general, there are three methods: survey, observation, and experiment. One example for the use of survey/observation is a FAA report regarding reducing the standard of runway separation [30]. FAA conducted a field test to study differences in ATC equipment that affect strategies of controllers at airports. After the observation, they surveyed ATCos to collect their opinions about the new standard. Recent studies involving human subjective experiments focus on human and computer interaction for future systems. Mercer et al., 2014 recruited ATCos to test the performance of the proposed traffic management system designed for expected future air traffic [31]. Rantanen and Nunes, 2009 experienced ATCos and college students to test their hypothesis regarding the actions [32]. These approaches have known limitations in generalizing their results. Overall, this type of approach requires expert participants, which have difficulties in recruiting participants due to a smaller pool size. Individually, results from the survey can be too generalized or different from what participants do. Also, participants of the human subjective experiments may not act as they are in the real situation due to controlled environments.

Research utilizing air traffic data use various types and state of it. Martin et al., 2016 generated air traffic scenarios based on flight plans and radar information [33]. Rantanen and Wickens, 2012 adapted specific cases of aircraft conflict data [34]. Also, studies like Reynolds and Hansman, 2005 are designed to use real-time data [35]. To study ATCo actions, Martin et al., 2016 conducted a human subjective experiment using their scenarios, while the other two studies analyzed the data directly under their hypothesis. The hypothesis from Rantanen and Wickens's 2012 is based on its previous studies that found preferences on the actions [36]. Based on the preferences, this study designed classes of ATCo actions and categorized each conflict according to them. The classification is based on recorded trajectories of aircraft, which involves lateral and vertical maneuvers. Another group of researchers studied based on a hypothesis about intentions behind aircraft that deviated from its original route [37–39]. These studies design a set of maneuver models that describe the intention of particular aircraft motion to predict corresponding ATCo actions. Recently, a similar group of researchers applies machine learning methods to classify ATCo actions [40]. This study developed a supervised learning-based method developed by using large-scale air traffic data.

3. PART 1: METHODS

The fundamental of collecting ATCo actions from the flight tracking data is in tracing back chronologically ordered series of events. These events imply how an ATCo maneuver an aircraft to resolve predicted aircraft conflict. Also, there are two assumptions associated with ATCos. Figure 3.1 illustrates these events and assumptions. The first assumption is about the CD&R process by ATCos. Chronologically, ATCo has to predict a pair of aircraft that are expected to cause conflict while monitoring air traffic from the assigned region. Then, the ATCo takes action to the current aircraft activities. This action includes a maneuver that makes pilots deviate their aircraft from the original route to avoid the predicted conflict. After the deviation is executed and operation is done, flown trajectories in the flight tracking data represents these changes. Another assumption is about the flown trajectories. The trajectories not only show how an aircraft flew, but also results of ATCo actions because aircraft must follow their actions. Based on these two assumptions, the proposed method tracing back flown trajectories of aircraft to find any deviation from their planned trajectories. The proposed method would consider a pair of aircraft as a predicted aircraft conflict if one deviated and another one is expected to cause a conflict within the deviated region. Then it considers applied deviation as an ATCo action to resolve the conflict.

The process to identify predicted aircraft conflicts and corresponding ATCo actions includes six significant parts: data collection and process, applied algorithms, aircraft filtration, and analysis. This method assumes flown trajectories of aircraft reflect air traffic management operations of ATCos. Thus, the proposed method collects and processes flight tracking data of aircraft that must be guided by ATCos. Two algorithms take the processed data. The algorithms identify deviations from aircraft's

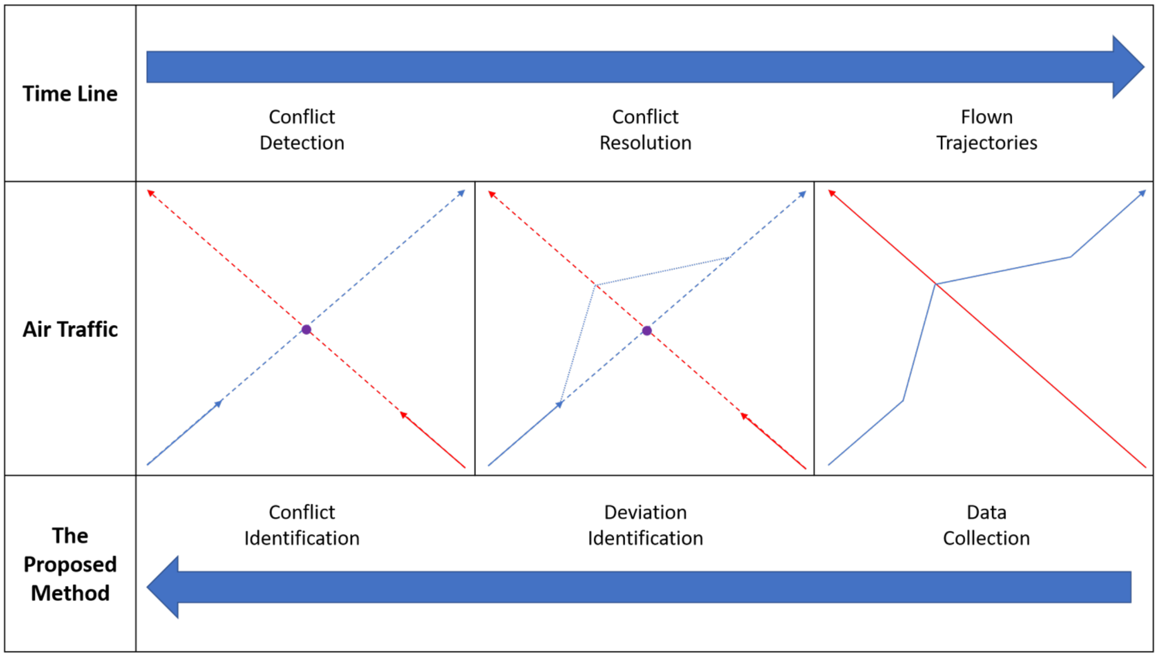


Figure 3.1.: An overview of Part 1: Methods

initial routes then search another aircraft to be paired for an expected conflict. Filtration techniques were developed to make the process efficient to manage a large-scale of the collected data. Lastly, the output from the algorithms is analyzed to inference ATCo actions and provide general statistical analysis of their characteristics.

3.1 Data Collection

FlightAware collects real-time flight tracking data from their automatic dependent surveillance-broadcast (ADS-B) ground stations. The data collection utilized two types of flight data that they collect from aircraft: the open and closed-loop data. Unlike a general flight plan, the open-loop data from FlightAware only includes a series of waypoint codes from departure to arrival. The codes can be decoded to provide their coordinates and other information. The open-loop data is always included in the transmitted data if an aircraft have them. However, the closed-loop data updates approximately every 30 seconds until its arrival. It includes eight variables: timestamp, latitude, longitude, speed, altitude, altitude change (whether an aircraft is climbing, cruising, or descending), altitude status (whether an aircraft is away from its ATC-assigned altitude), and update type (how the information was updated). With the closed-loop data, heading and pitching angles can be calculated by projecting the records.

The data collection targeted the high-altitude of airspaces for three air traffic control centers. Selected zones are ZLA (Los Angeles), ZOB (Cleveland), and ZTL (Atlanta). These sectors are selected due to their traffic density. Logically, there is a higher chance of having conflicts if there are more aircraft at a place at the same time. Also, if the method cannot find a conflict from those airspaces, it will not find from other places also. Additionally, aircraft flying at high-altitude sectors have open-loop data. According to the regulations, IFR aircraft must possess flight plans to fly in the high-altitude sector.

A query tool was developed to collect the data automatically. It continuously monitors real-time information from FlightAware. The query tool must specify an area and an altitude to scan aircraft within a targeted space. Shapes of the airspaces are complicated polyhedron, as presented in Figure 3.2 in orange lines. Search boxes were created to wrap the target airspaces based on the minimum and maximum latitudes and longitudes of each space, as shown in Figure 3.2 in red lines. Since the boxes include spaces that are not the targeted spaces, it could include aircraft that did not pass the target airspaces. Additionally, searching altitude is set to be above 250FL, which is the minimum altitude of high-altitude sectors.

The first task of the query tool is scanning unique identification (ID) of aircraft instead of their open and closed-loop data. The scanning process only captures the flown trajectories from the departure to the moment. Therefore, the tool initially collects their IDs only until the scanning is over. The second task is retrieving open and closed-loop data by searching the database of FlightAware with the collected IDs. The tool performs the scanning task every 1 minute. For continuous and secure

Figure 3.2.: A visual example of the boxed airspace (ZOB)

scanning, the query tool was operated on Amazon Web Service that provides an on-demand cloud platform.

3.2 Data Processing

The open and closed-loop data collected is not processed. Eight cleaning processes were conducted to filter un-usable ones. Frist process is identifying empty data. Sometimes quarried ID does not contain any information, or either open or closed-loop data does not exist. The first process identifies these three cases of empty data and removes them from the list. The second process matches open and closed-loop data. Some empty close and open-loop data is removed from the previous process. Thus, the second process needs to make sure that both types of data are there for an aircraft. If an aircraft does not have one of them, it was filtered.

From the third process, the rest of the cleaning process checks content in each type of data. Even though the flight data was queried by altitude above 250FL, it is still possible that recorded data may be different. The third process checks all closed-loop data to make sure that aircraft were recorded to fly at high-altitude. The fourth process checks whether there is an empty data point in both types of data. Sometimes un-processed data records a data point twice. The fifth process checks any duplicated data point by comparing the predecessor and successor of each data point.

Occasionally, an aircraft may not arrive at the designated airport due to various reasons. In this case, a flight plan is no longer valid for the proposed method. Also, it is possible that the submitted flight plan may have different departure points. The sixth process compares the departure and arrival points of the closed and open-loop data. Each raw of closed-loop data is collected approximately every 30 seconds. If data contains a value that exceeds maximum projection from the previous state, the seventh process checks if the value can be adjusted. If the situation occurs consecutively, corresponding data is excluded.

The last process investigates fluctuations in recorded speed and altitude of aircraft. Closed-loop data present the speed of aircraft in terms of ground speed. As the ground speed includes wind speed, it fluctuates over the period while aircraft is in constant airspeed. This fluctuation affects the performance of the deviation detection algorithm. Since the collected data does not include wind information, this process stabilizes collected speeds by averaging them. Figure 3.3 shows the raw and processed speed of an aircraft from departure to arrival. It averages ground speeds every 5-minute intervals, which is equivalent to 10 consecutive data points. Recorded altitudes were tested with the same method.

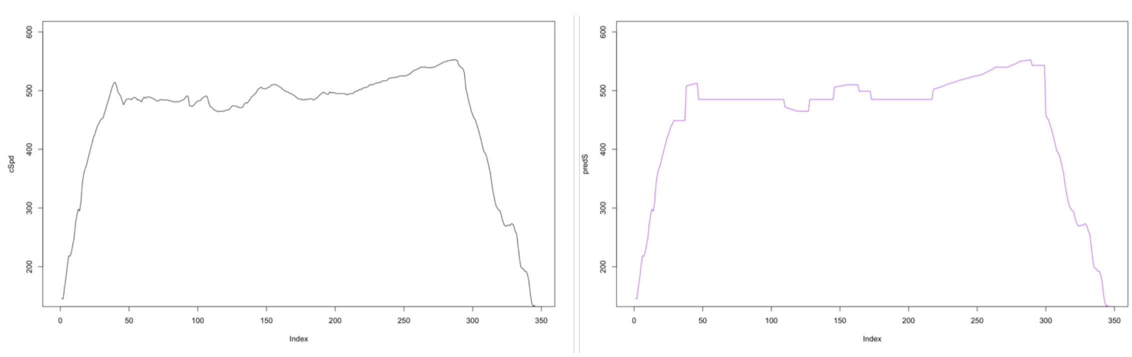


Figure 3.3.: A visual example of the speed leveling

3.3 Deviation Detection

In this work, a deviation is defined as a difference between the flight plan and flown trajectories. Detecting a deviation of an aircraft is one of the significant algorithms developed for Part 1. A deviation can be calculated because of the unique characteristics of flight operations. In general air traffic operations, ATCos put a deviated aircraft back to its original route and status when predicted conflict is resolved. Logically, an aircraft must come back to its original route if its arrival airport does not change. This part defines an area generated by initiating a deviation and closing by returning to the planned operation as a deviated region. An aircraft can deviate from its flight plan in terms of three different dimensions: lateral, vertical, and speed. It can deviate with changes in one or more of the listed dimensions at the same time. Different method is required to detection deviations in each dimension. Notably, the deviation detection algorithm is heavily dependent on a distant calculation between two points on the surface of the earth. A Geodesic calculation on ellipsoid WSG84 is applied to calculate the shortest distance between two coordinates [41]. To calculate distance from deviated trajectories to the first ones, the off-track distance calculation that calculates the shortest distance between a point and a line segment was used.

3.3.1 Lateral deviation

Figure 4 illustrates the detection of lateral deviations. Both open and closed-loop data includes coordinates, and a combination of latitudes and longitudes explains the lateral dimension. Coordinates in open-loop data are the waypoints that an aircraft is planned to pass, but those in closed-loop are recorded locations that an aircraft was positioned. Coordinates of closed-loop data are recorded approximately every 30 seconds. Thus, open-loop data have a much smaller number of coordinates compare to those of the closed-loop data. They were meant to be connected to generate a planned route.

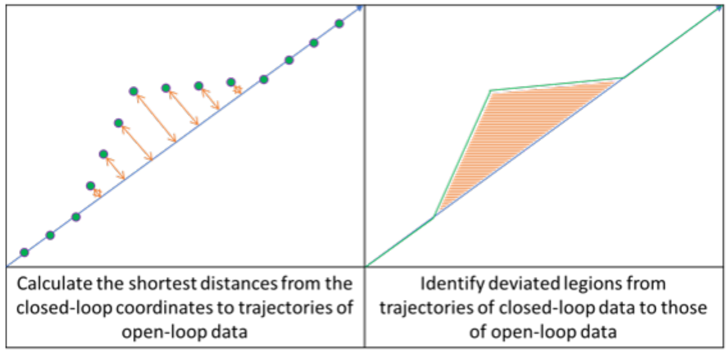


Figure 3.4.: A visual example of the lateral deviation detection

The algorithm for the lateral deviation calculates a distance from those closed-loop data to a planned route generated by the open-loop coordinates. The algorithm first generates segments out of open-loop waypoints. A segment is a straight line between two consecutive open-loop waypoints. Then, it calculates a distance from a closed-loop coordinate to the generated segments. Equation 1 shows a calculation of the distances; it calculates a geodesic between a segment of open-loop waypoints and a closed-loop coordinate. The equation computes a triangle by connecting the first open-loop waypoint to the closed-loop point then projecting perpendicular line to the segment between the waypoints. After calculating distances for each segment, the algorithm picks the minimum value from the distance list. For one closed-loop coordinate, the algorithm generates several distances, which is equivalent to the number of segments in open-loop waypoints. The selected distance is the shortest distance from a closed-loop coordinate to its planned route. Also, it shows how much a closed-loop coordinate has deviated from its planned route. If the distance is zero, it implies that the aircraft was on the planned route at that moment. The algorithm loops this calculation to every coordinate in the closed-loop data on those of open-loop waypoints. As a result, the algorithm generates how far each closed-loop coordinate has deviated from the planned route by open-loop waypoints.

After the distance calculation, the algorithm finds a deviated region. It searches for a series of coordinates that the distances were continuously increasing until a certain point then decrease back to the planned route. Even though an aircraft is trying its best to stay on the planned route, it can be slightly off the track due to other circumstances such as weather, recording, and calculation errors. The algorithm neglects any deviation of fewer than fifty meters to mitigate this issue. Also, the algorithm only considers deviations that consist of at least two consecutive points. Identified two consecutive deviations are equivalent to four consecutive records, approximately 2 minutes of flight operation, by adding additional points to the front and back. These additional points act as the starting and returning points.

Altitude and Speed deviations

Algorithms to detect deviations in vertical and speed dimensions are different to that of lateral deviations. Both open and closed-loop data include lateral information. However, collected open-loop data does not include planned altitudes nor speeds at specific waypoints. Thus, there is no base value from open-loop data to perform a comparison against that of closed-loop data. The algorithms use the status of an aircraft when it is in the cruise phase, steady-state, as a base value for the comparison. In a flight operation, ATCo assigns an altitude and airspeed to an aircraft for cruising after it finished to ascend and enter a high-altitude sector. The steady-state is unknown, but the algorithm finds it from the closed-loop data. Figure 3.5 illustrates the process to identify the steady-state. The algorithm looks for at least ten consecutive records that have identical altitudes and speeds. The region enclosed by two red dotted line is the identified steady-state. The green dotted line represents 250FL, which is the minimum altitude for the high-altitude airspace sectors. Instead of the recorded speed, the algorithms take leveled speed from the Data Processing. Ten consecutive records are equivalent to 5 minutes of flight operations. If they cannot find any steady-state, it looks for one less consecutive records until the searching range becomes two consecutive records. Also, if they find multiple sections of closed-loop data that satisfy the conditions for a steady-state, the algorithms select the earliest one. Once a steady-state of an aircraft is determined, the algorithm uses the values to find any deviations in corresponding dimensions.

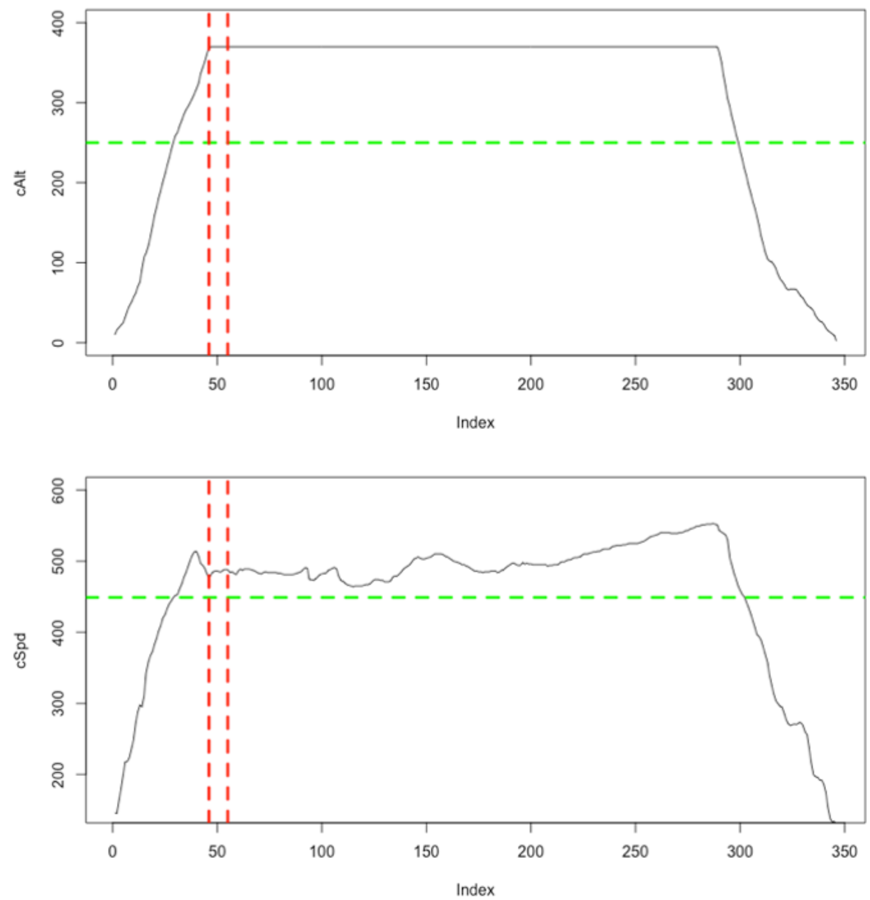


Figure 3.5.: A visual example of the steady-state calculation

Figure 3.6 illustrates the process of altitude and speed deviation of detections. The algorithms find the difference between the steady-state and recorded altitude and speed separately. Unlike the lateral detection, it only checks from the time when an aircraft entered a high-altitude sector when it is flying above 250FL. Similar to the lateral detection, the algorithms search regions where altitude and speed either increase above those of aircraft's steady-state and return to it. Since altitude and speed can be decreased, the algorithms also look for the reversed deviations. The deviated regions also must be longer than two consecutive points.

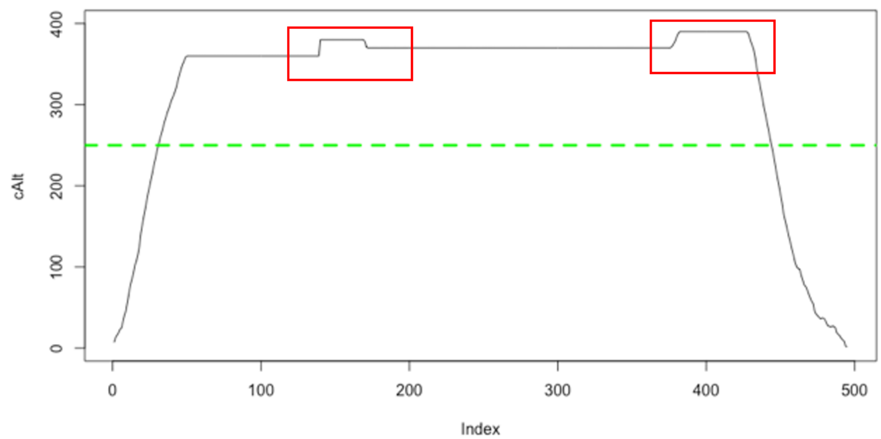


Figure 3.6.: A visual example of the altitude and the speed deviations

3.4 Conflict Detection

The conflict detection algorithm takes the deviated region collection from the previous algorithm to predict an aircraft conflict pair. Figure 3.7 illustrates the process of the algorithm. First of all, the algorithm boxes the lateral dimension of the deviated region regardless of deviated dimensions. A pair of aircraft is expected to violate a separation, and it needs to violate both lateral and vertical separations to cause a conflict. The algorithm finds any other aircraft that passed the boxed deviated area to check the lateral separation first. The box is generated by the maximum and minimum values of longitudes and latitudes from the closed-loop coordinates that correspond to the deviated region. After the box is generated, the algorithm stretches the box by 1 degree from both latitudes and longitudes on both sides. The stretching is a technique to widen the searching area. It is critical in a case where the deviated region is relatively small or narrow. For example, lateral deviation results in a polygon defined as a deviated region. However, if an aircraft deviated by changing either altitude or speed, the enclosed region can be a line in the lateral dimension. Then, the algorithm cannot find any other aircraft because the searching region does not exist. After stretching the box, the algorithm searches any other aircraft that their closed-loop data passed the region. After collecting a list of aircraft that passed the boxed area, the algorithm checks the vertical dimension of the aircraft. It removes aircraft that was not in the high-altitude sector. It filters aircraft that did not enter a high-altitude sector, above 250FL, during their flights inside of the box.

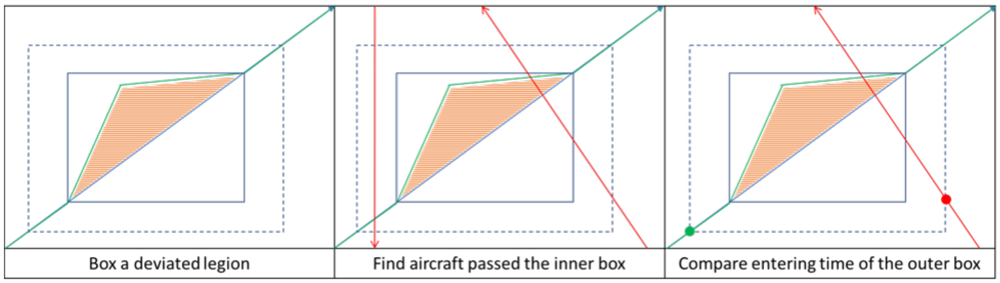


Figure 3.7.: A visual example of the altitude and the speed deviations

After the lateral and vertical filtration, the algorithm checks how close the other aircraft is to the deviated one. The distance calculation from the deviation detection was adapted for the calculation. The algorithm calculates the shortest distance between open-loop coordinates of the deviated aircraft and closed-loop coordinates of the second aircraft within the box. In lateral deviation, a deviated aircraft will no longer have a lateral separation violation. It is expected to fly on the planned route, so the closed-loop coordinates are on those of open-loop. In a vertical violation, both aircraft also must violate lateral separation. For the speed, the violation can be either one. After calculating the shortest distances between them, the algorithm checks whether the distance violates a lateral separation. If it does violate the rule, the open-loop position of the deviated aircraft and closed-loop position of the second aircraft is considered as conflict points. If the distance does not violate the rule, the second aircraft was not considered for a conflict pair. Lastly, the algorithm calculates arrival time to the conflict points. The second aircraft directly use its corresponding timestamp from its closed-loop data. For the deviated aircraft, both vertical and speed deviations directly use corresponding timestamps. In the case of the lateral deviation, the algorithm takes the timestamp of closed-loop data. It takes timestamp from the deviated points that are perpendicular to its conflict point as predicted arrival time. The algorithm calculates the difference between the two arrival times. If the difference is less than 5 minutes, the corresponding aircraft is considered as a predicted aircraft conflict pair.

3.5 Data Filtration

The purpose of utilizing flight tracking data to collect ATCo actions is in the collection of large-scale data efficiently. Methods used in this part includes trigonometric calculations and various nested loops. As a result, each calculation takes a long computational time. Special techniques were developed for efficiency. These techniques apply filters to the data so that each calculation does not have to be conducted on every entity. The first technique was specifying the closed-loop data when the target aircraft was flying in the target airspace. Aircraft can be passing, arriving, or departing to the airspace. Since the study is only interested in the target airspaces, it does not need to worry about the rest.

Additionally, airspace in and out the time of an aircraft is collected to filter other aircraft that did not fly in the same airspace at the relatively same time. Average flight time is calculated for each airspace to come up with a filter window. This value was subtracted from the airspace in time and added to the time for airspace out.

The second technique goes along with the previous one. It locates closed-loop trajectories that were above 250FL to make sure deviation detection calculations to be conducted when aircraft were on high-altitude sectors and the en-routing phase. These two techniques help to narrow down meaningful processing data from the deviation detection. The last technique helps to find candidates for the conflicting pair. When the box for a deviation region is stretched, recorded timestamps representing entering and exiting the box by a deviated aircraft and other aircraft can be calculated from their closed-loop data. The calculation is finding the closest recorded points to the borders of the box. This technique reduces the number of conflict pair candidates and decreases the load on calculation for the predicted aircraft conflict pairing.

3.6 Categorical Analysis

Analyzing collected data includes two significant methods. The first method investigates collected controller actions to decide whether its corresponding conflict was resolved by one action or else. The deviation detection algorithm finds deviations in three different dimensions separately. It is possible that an aircraft conflict was resolved by either one action or multiple. The first method finds unique pairs. It separates collected data into two groups: one with a single maneuver and another with multiple maneuvers. If a pair is detected times, the analyzing method checks their deviated regions. If some portion of the regions are overlapping or one region either identical or belongs to another, the corresponding pair is considered to get a mixed maneuver from their ATCo.

The second method categorizes the collected actions based on their characteristics. Based on literature reviews, the categorization results forming the actions into a hierarchical structure with three layers. Table 1 describes the categorization. The top layer is the target layer. Each ATCo action is categorized to specify targeted aircraft from the corresponding pair. Distances between a predicted point and a conflict point were used to standardize the target. Predicted point is defined as the location where a deviated aircraft started a maneuver. Since untargeted aircraft did not deviate, recorded points with the least difference in recorded time are considered as its predicted point. Thus, aircraft are categorized into four groups in this layer: closer to conflict and targeted, closer to conflict and un-targeted, not closer to conflict and targeted, and not closer to conflict and un-targeted. The following layer, Type, corresponds to how an aircraft has deviated. It directly utilizes the three dimensions applied to collect deviations. This layer has three groups based on deviated dimensions: lateral, vertical, and speed. The last layer deals with specifics of the applied type maneuver. From the literature review, many different options were existed to apply a maneuver. Those options can be categorized into two groups. One option eventually reduces a value that has a direct relationship with the corresponding dimension of the Type and vice versa. For example, all options that result in reducing speed correspond to a group and increasing to another. Travel distance is the base value for lateral deviations, and altitude is that of vertical deviations. General statistics were applied to calculate the portion of each layer and its groups.

4. PART 1: RESULTS

4.1 Data Collection

Flight tracking data was collected from January 14 to 18 of 2019. The data must be collected by a given access code to use the database of FlightAware. Also, the given access code is only valid for specified days assigned by the provider. The access was only provided for three days due to the company's policy. Also, it can only be provided during work hours. Thus, initial access to the database was from January 14 to 16 of 2019. However, the access was extended additional three days from January 16 due to a technical issue that occurred on that day. As a result, the data collection period became five consecutive days.

The data was collected from three US airspaces: ZLA (Los Angeles), ZOB (Cleveland), and ZTL (Atlanta). The data was collected from those five consecutive days, which is equivalent to 120 flight operation hours. During the time, the data was queried from the database of FlightAware. The targeted airspaces were queried 7,200 times. Figure 4.1 shows an overview of the collected flight tracking data. About the same number of aircraft activities were collected across the airspaces: ZLA with 3,644 aircraft, ZOB with 3,454 aircraft, and ZTL with 3,499 aircraft. In total, activities of 10,5097 aircraft in high-altitude sectors of the target airspaces were collected.

Figure 4.2 shows the daily analysis of the collected data. Except for day1 and day4, a similar number of aircraft were flown in each airspace. The low total number of flights on day1 is caused by the data collection time that started from the afternoon of the day. Thus, it lost about half of the flights on the day. Besides the total number of daily flights, each airspace shows similar results on each day.

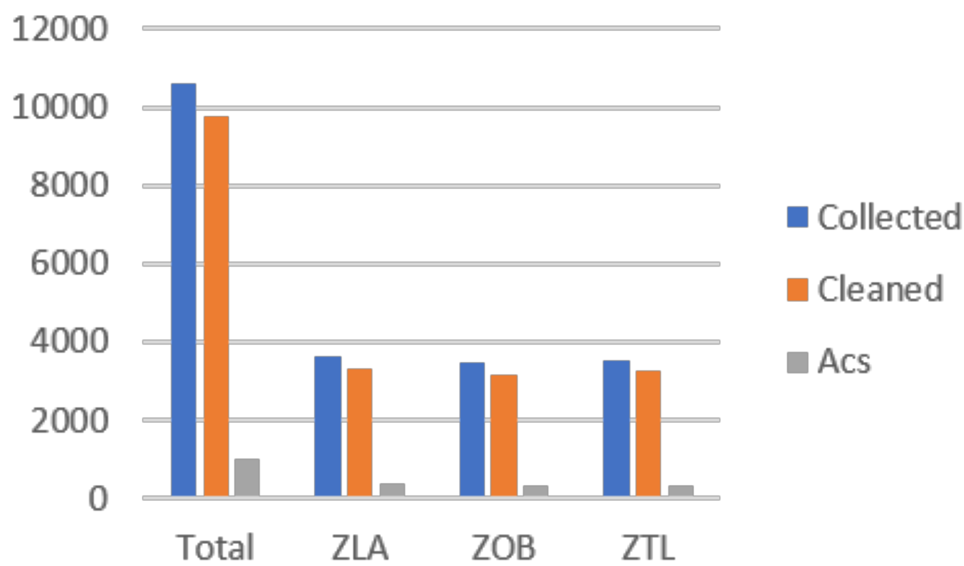


Figure 4.1.: An overview of Part 1: Results

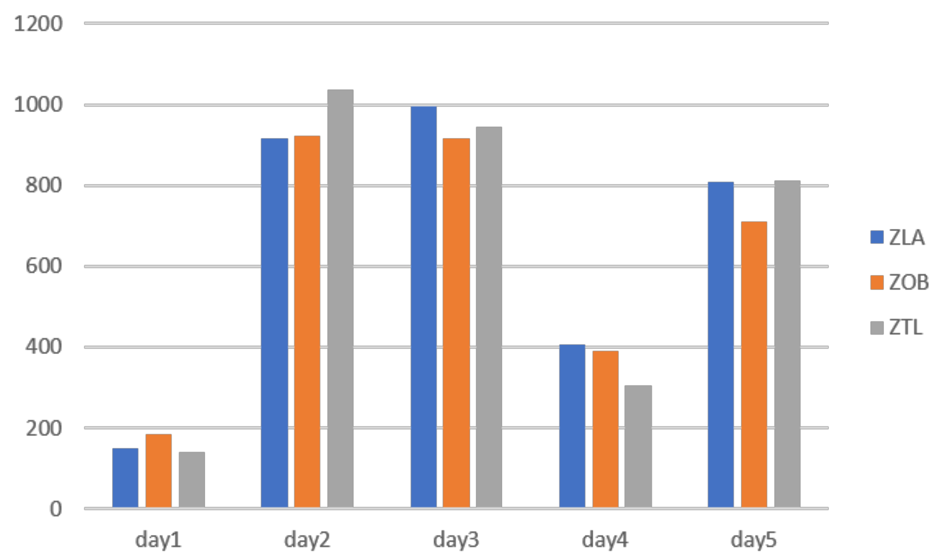


Figure 4.2.: A daily analysis on the overview of Part 1: Results

4.2 Data processing

The data cleaning process filtered 848 aircraft from the list, which is about eight percent of the collected data. Two types of collected data corresponded to the filtered data. The retrieved flight identification did not include either open or closed-loop data. The search query was conducted to find aircraft that have flown on the high-altitude sectors of the targeted airspaces. The high-altitude airspace sectors locate above 250FL. However, the closed-loop data of some aircraft did not include any locational information that indicates they were flying above 250FL. The cleaning process identified other issues that can be corrected. Some open-loop data included duplicated waypoints. Those points were removed from the open-loop data. Lastly, both open and closed-loop data do not show any omitted data points. As expected from the methods, speed from the closed-loop data showed continuous fluctuation. They were leveled by identifying steady states of each aircraft. The altitudes recorded in the closed-loop data did not show fluctuations like the speeds; the methods did not level them.

4.3 Deviation Identification

After the data processing and filtration, the deviation identification algorithm found 69,300 deviations from the collected data. Figure 4.3 shows the results of the algorithm. The algorithm found over twenty thousand deviations from each airspace. The total number of lateral deviations is slightly less than twenty thousand, while those of vertical and speed deviations are about twenty-five thousand each. The proportion of altitude deviations is the largest among them. Each airspace shows similar trends: the proportions of lateral deviations are the least, while those of altitude deviations are the largest across the airspaces. In total, these deviations were identified from about twenty-five thousand aircraft. About three thousand aircraft were identified by the algorithm across three deviation types and airspaces. There are about nine thousand unique aircraft, which is about ninety percent of the collected aircraft. On average, an aircraft deviated three times during its flight operation regardless of the deviation type.

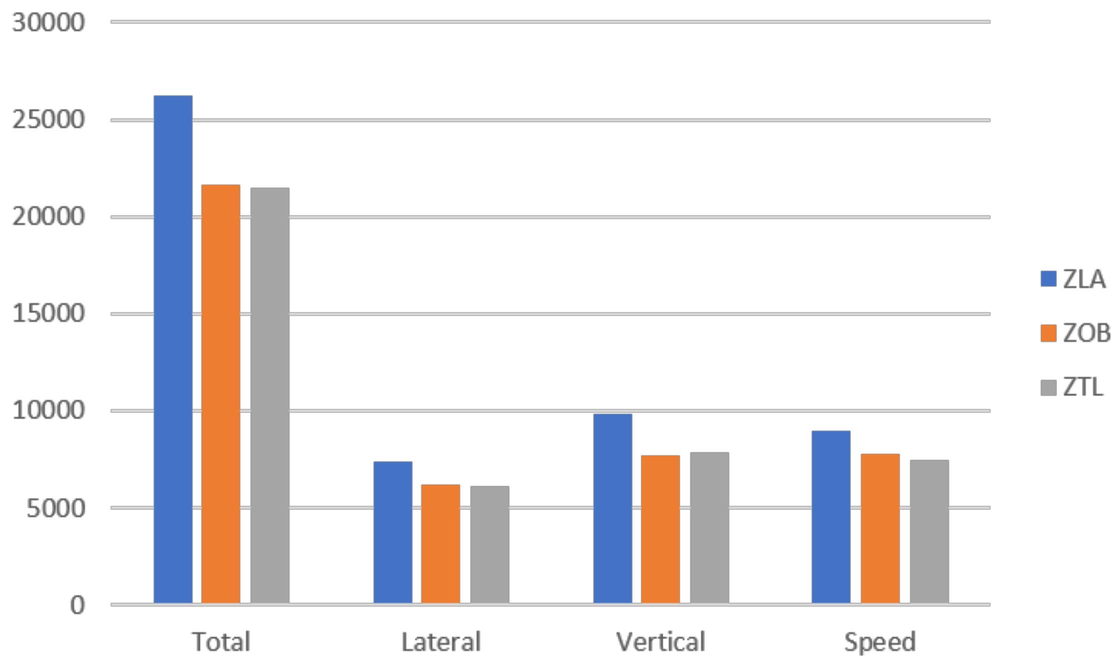


Figure 4.3.: An overview of the deviation identification

4.4 Conflict Identification

Figure 4.4 shows the identified conflicts and ATCo action. The conflict identification algorithm identified a total of 1,312 individual predicted aircraft conflicts. In detail, 418 conflicts from ZLA, 427 from ZOB, and 467 from ZTL were identified. The identified 1,312 conflicts were caused by 1,238 unique predicted aircraft conflicts. ZLA resulted in 360 unique aircraft conflict pairs, ZOB resulted in 409 pairs, and ZTL resulted in 469 pairs. The number of identified individual predicted aircraft conflicts are less than the number of unique aircraft conflict pairs. It implies that there are conflicts that ATCo applied multiple maneuvers. In total, 914 conflicts were resolved with a single maneuver, while 324 conflicts involved more than one maneuver. In ZLA, there are 147 single-maneuver conflicts and 89 multiple-maneuver conflicts. ZOB has 125 single maneuvers, and 107 conflicts with multiple maneuvers. Lastly, ZTL has 126 single maneuvers while there are 128 multiple maneuvers. There is a small difference between ZLA and ZOB and ZOB and ZTL. However, the difference between ZLA and ZTL is slightly bigger. In percentages, the difference among the airspaces is less than four percent. Both ZLA and ZOB showed a bigger portion in single maneuvers, while ZTL has slightly more cases on the multiple maneuvers.

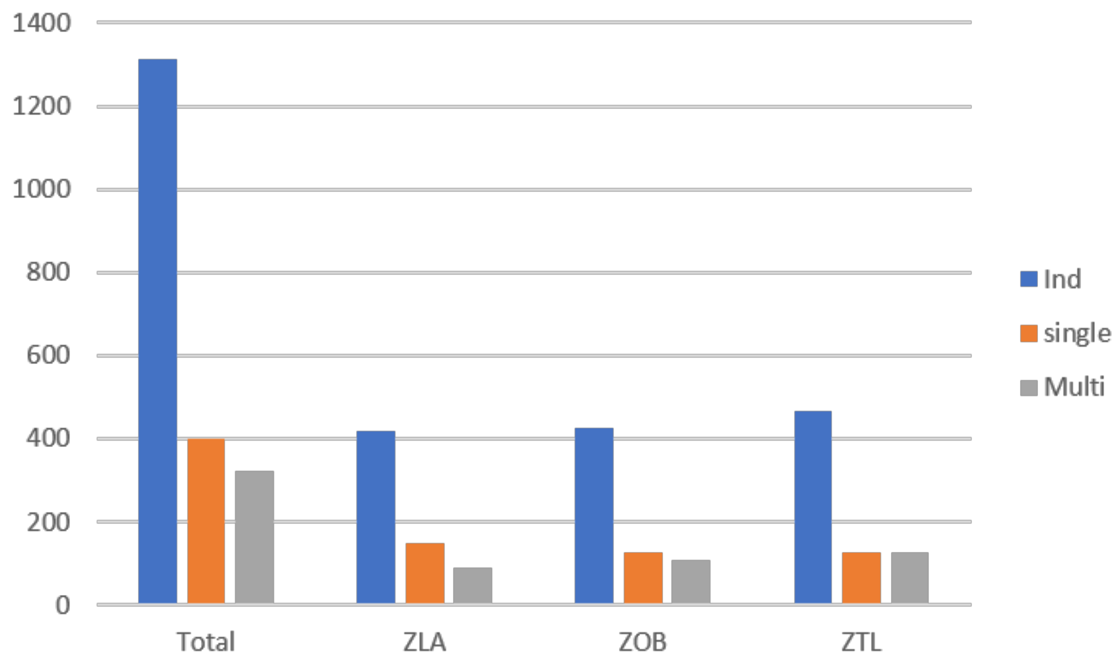


Figure 4.4.: An overview of the identified aircraft conflicts

Figure 4.4 shows the proportions of unique aircraft in the identified aircraft conflicts. There are 2,624 aircraft that are involved in the identified aircraft conflict pairs. However, there are 831 unique aircraft in pairs. It implies that there are aircraft involved in more than one conflict, even considering the multiple maneuvers. ZLA has 194 unique single maneuvers aircraft and 128 unique aircraft for multiple maneuvers. ZOB has 158 unique aircraft for single and 139 aircraft for multiple maneuvers, while ZTL has 163 and 173 for the corresponding types. These results also tell that about thirty to forty percent of the total aircraft conflicts include aircraft involved in another conflict across the airspaces. The discussed ratio between the mathematical number of aircraft involved in the conflicts and those of the unique number of aircraft on the singles and multiples are within ten percent difference.

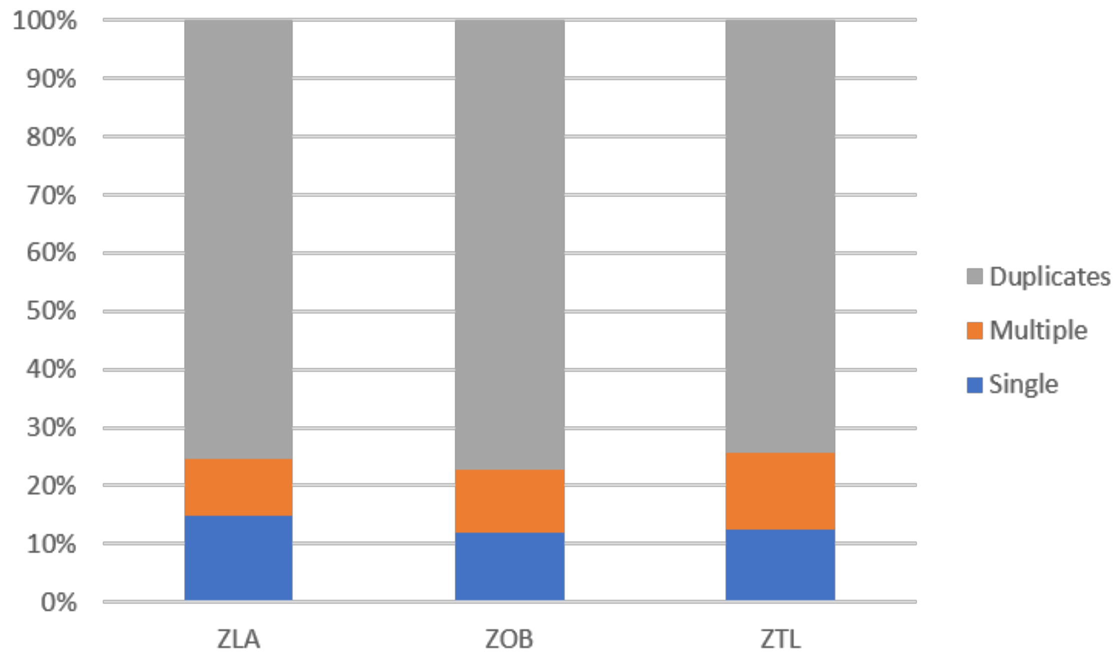


Figure 4.5.: An overview of the identified aircraft conflicts

4.5 ATCo action categorization

Table 4.1.: An overview of the individual air traffic controller actions

<table>
<tr><td colspan="2" rowspan="2">Target</td><td>Lateral</td><td>Vertical</td><td>Speed</td></tr>
<tr><td>358</td><td>472</td><td>482</td></tr>
<tr><td rowspan="2">Closer
AC</td><td rowspan="2">708</td><td>166</td><td>132</td><td>171</td></tr>
<tr><td>52</td><td>118</td><td>102</td></tr>
<tr><td rowspan="2">Further
AC</td><td rowspan="2">604</td><td>45</td><td>88</td><td>83</td></tr>
<tr><td>128</td><td>134</td><td>126</td></tr>
</table>

Table 4.1 shows the categorized ATCo actions counted individually. The difference between the selected target is less than ten percent. The proportions among the type maneuvers show portions of both vertical and lateral maneuvers are similar while lateral is slightly smaller. The proportions of option maneuvers show some clear differences. The numbers on the top cells represent negative options while the bottom ones represent positive options. For targeting aircraft closer to their conflict points, negative options of each type of maneuver were more used. However, the difference from vertical is smaller than the other two maneuver types. For targeting aircraft further away from their conflict points, positive options were used more frequently than the negative ones. These results show that different from option selection depends on the target selection regardless of the selected type maneuvers.

Table 4.2 shows the results of each airspace. The trends from Table 1 can also be observed from the data. However, results from ZOB has a slight difference in their option maneuvers. Unlike other airspaces, ATCos from ZOB selected positive options more when the targets are the closer aircraft, and the selected type maneuvers are vertical.

Table 4.3 shows the categorized ATCo actions that only involve single maneuvers. Like the individual maneuvers, the closer aircraft were selected more often. The difference between the proportions of the selected target is even greater than that of the individuals. Also, the speed maneuver takes the largest portion among type maneuvers. The option maneuvers showed similar trends as the individual ones. The only difference can be found from the proportions of options for speed maneuvers when the further away target is selected.

Table 4.4 shows the categorized ATCo actions involving single maneuvers for each airspace. The categorized actions from each airspace also show similar trends. The results from ZOB has the least difference between the selected target. There are small differences, but the trends in proportions of the type maneuvers show identical results. The trends in the option maneuvers show generally similar trends. In the options for the vertical maneuvers, others have the same trends except for those of

Table 4.2.: An overview of the individual air traffic controller actions by each airspace

Airspace	Target	Lateral	Vertical	Speed
ZLA		108	164	146
Closer AC	232	48	59	57
		14	30	24
Further AC	286	15	34	33
		31	41	32
ZOB		117	145	165
Closer AC	222	37	33	61
		14	43	34
Further AC	205	16	23	27
		50	46	43
ZTL		133	163	171
Closer AC	254	48	40	53
		24	45	44
Further AC	213	14	31	23
		47	47	51

Table 4.3.: An overview of the single-maneuver air traffic controller actions

Target		Lateral	Vertical	Speed
		115	122	161
Closer AC	251	41	51	82
		25	32	20
Further AC	147	13	15	35
		36	24	24

Table 4.4.: An overview of the single-maneuver air traffic controller actions by each airspace

Airspace	Target	Lateral	Vertical	Speed
ZLA		39	46	62
Closer AC	96	17	26	30
		8	8	7
Further AC	51	6	5	16
		8	7	9
ZOB		39	36	50
Closer AC	73	11	11	27
		8	12	4
Further AC	52	3	5	9
		17	8	10
ZTL		37	40	49
Closer AC	82	13	14	25
		9	12	9
Further AC	44	4	5	10
		11	9	5

ZOB. It also shows opposite trends on the speed maneuvers while selecting the further away targets.

Table 4.5 shows categorized ATCo actions with multi-maneuvers. Unlike the individual and single maneuvers, multi-maneuvers were categorized based on the selected target and the combination of maneuvers. It shows that there is no significant difference between target selection. From the results, the combination of vertical and speed maneuvers and all together are used the most regardless of the targets. Table 4.6 shows the results of each airspace. Each airspace has differences in the multi-maneuvers. In ZLA, combinations between lateral and vertical and lateral and speed

Table 4.5.: An overview of the multi-maneuver air traffic controller actions

Target	Lateral + Vertical	Lateral + Speed	Vertical + Speed	All
	12	13	23	123
Closer	20	30	51	42
Further	18	19	50	66

on closer targets were applied more often than the further away ones. However, the opposite trend appears on the other two combinations. In ZOB, only the combination between vertical and speed maneuvers on the closer targets was more used, but other combinations result differently. In ZTL, the combinations between lateral and vertical, and vertical and speed on the closer targets were applied more than the future ones. Other combinations show an opposite trend. Unlike individual and single maneuvers that do not have any significant differences among the airspaces, the categorization of multi-maneuvers shows regional differences.

Table 4.6.: An overview of the multi-maneuver air traffic controller actions by each airspace

	Lateral + Vertical	Lateral + Speed	Vertical + Speed	All
ZLA	16	12	29	26
Closer	10	9	12	9
Further	6	3	17	17
ZOB	8	12	36	42
Closer	2	5	20	17
Further	6	7	16	25
ZTL	14	25	36	40
Closer	8	16	19	16
Further	6	9	17	24

5. PART 2: METHODS

Existing prediction models have never been validated against ATCo actions. The introduction discussed one reason, which is the absence of actual ATCo actions. Not only the ATCo actions but also the corresponding predicted aircraft conflicts are required for validation. The validation can be accomplished by comparing them. Also, actual aircraft conflicts are required for the comparison because it must be between solution from the model based on a conflict against ATCo action for that conflict. Part 1 collected both ATCo actions and corresponding predicted aircraft conflicts. Part 2 utilizes the collected information to evaluate an existing prediction model on ATCo actions. The evaluation includes three contents. First, existing prediction models must be listed and select one to evaluate. The selected model must satisfy a series of conditions so that it can be properly evaluated. Then, the model is transformed into a form that can take the collected aircraft conflict. The transformation is required not only to take the designed input but also to generate solutions that enable comparisons. Three different measurements were applied to provide a comprehensive evaluation of the performance of the model. The first measurement, qualitative comparison, categorically compares model solutions against ATCo actions. The second measurement, feature comparison, identifies causations of differences between them. The third measurement, quantitative comparison, checks the applicability of model solutions to the conflicts, which is having ATCo actions different from the model solutions.

5.1 Model Selection

Researchers have studied CR for a long time. From the studies, many models are developed and reviewed. Part 2 of this work selected an existing model for evaluating its performance against ATCo actions on the corresponding predicted conflicts. The evaluation was conducted on one of the models instead of multiple of them. This kind of evaluation has never been conducted before, and conducted methods are novel. Also, the conducted method is not designed to be case-specific. The methods can be applied to other models if they satisfy a set of conditions.

The first step for the model selection is collecting a list of them. Keywords related to CR was used to search literature about the models. After locating literature describing the models, characteristics of the models were listed. The second step checks eligibility of the listed models to see whether they are capable of being evaluated. A series of conditions must be satisfied to proceed with the evaluation process. Following list shows the major conditions that the candidates must satisfy to be considered.

- A model provides a solution for en-routing aircraft
- A model provides a solution for aircraft conflict pairs
- A model is based on a human-subjective study
- A model solution is executable
- A model can take input information in a format
- A model has a structured process for solution generation

Part 1 collected ATCo actions and their corresponding predicted aircraft conflict pairs on high-altitude flight operations. Aircraft in this type of operation is in the en-routing phase. It collected the data on aircraft in this phase only due to its applied algorithms. The algorithms include a comparison between open and closed-loop data to find ATCo actions, and their conflicts and aircraft planned to fly at high-sector altitude must possess open-loop data by air traffic regulations. Thus, the collected data cannot be applied to the models that are not developed for en-routing aircraft. Aircraft conflict is defined as a conflict involving more than two aircraft. There are models focused on complicated conflicts involving multiple aircraft. The data collection from Part 1 did not consider complicated conflicts. Thus, models for those conflicts cannot be evaluated against the collected data. Besides human subjective approaches to develop the models, other researchers took mathematical approaches. Their studies consider aircraft conflict as a trigonometric problem by substituting movements of aircraft as vectors. These models also provide reasonable solutions. However, their solutions have a week relationship with ATCo actions due to the fundamentals of the models. Also, they do not contribute to the knowledge about ATCo, which is the main purpose of this work. Lastly, the mathematical approaches are out of the scope because this work is targeted to suggest new directions to the conventional human subjective approaches to studying human controls.

Existing prediction models have a wide range of fidelity. Some models can provide precise trajectories, while others suggest vague solutions. Part 2 defines a fidelity of the models by three abilities of the models. The first ability to check is the quality of solutions from the models. The solutions must be executable. For the comparison, the model solutions must be in a format that can be transformed in terms of the categorization of the ATCo actions applied from Part 1. A model should provide some information about target aircraft and maneuvers. For example, if a model solution is "change altitude," the model fails the condition because it does not provide a target. Also, if another solution is "deviate a slower aircraft," the corresponding model does not qualify due to the absence of a maneuver. The best case is a model that can provide at least a target and type from its solution in terms of the categorization methods applied in Part 1. The clarity in input information is another essential characteristic that affects a model's fidelity. Generating model solution to compare with an ATCo action, they must originate from identical aircraft conflict. If the information required to generate a solution is unclear, a conflict cannot be adequately utilized. For example, if a model's input is defined as "low traffic," it does not qualify because both "low" and "traffic" is relative and vague terms. However, there is an exception to the qualification if a model provides the following types of information on the side. It should provide how those terms are defined in the study, such as an area around a target to calculate traffic and a numeric scale for the traffic density. Also, the required input for a model could be generated from the collected data. Lastly, a model must have a structured process of generating solutions. A model becomes a black box without this information, and it cannot be transformed for the evaluation. For example, if a model states "use current altitude of an aircraft to change its speed," how to process altitude to make a solution is unknown. Thus, at least any description that can be transformed into if-statement must be provided, such as "if the current altitude of an aircraft is above 350FL, increase the speed of aircraft."

Many of existing prediction models can satisfy the discussed significant conditions. A list of minor conditions was applied to narrow down the model candidates qualifying the significant conditions. The significant conditions are designed to focus on essential capabilities for the evaluation against ATCo actions. However, the minor conditions deal with the expected performance of the selected model on the evaluation. A comprehensive model will be favored among the candidates. The performance of a model is highly dependent on its limitations. First, a model that can be applied to aircraft in various situations. If a model can only be applied to a specific case, the total portion of the aircraft that can be evaluated decreases accordingly. For example, if a model can only resolve aircraft conflict pairs that are cruising, any conflicts involving ascending or descending aircraft cannot be considered. It also directly related to the constraints that a model has regarding their statuses, such as altitude and speed. For example, the model does not have any constraints on the altitude of aircraft to be applied favored than others with such restrictions. Not only the range of situations and the number of constraints but also the range of solutions affect the model selection. According to Part 1, an ATCo action can be categorized into at least twelve different maneuvers. If a model can generate solutions for various targets and types of maneuvers in terms of the categorization method applied in Part 1, the probability of better performance on the evaluation compares to other models.

There are other aspects to consider other than the limitations of the prediction models. A model based on ATCo in the United States will be favored among the candidates. There are international flight operation regulations, but each country manages airspace by itself. Thus, differences in resolving aircraft conflicts can be expected among ATCos from different countries. The data is collected from US airspaces, and it is more likely to results in better performance with the models developed by studying US ATCo actions. The model reflects the characteristics of US ATCo, which also can be expected from the collected ATCo actions.

Along with a source of the candidates, how a model was conducted is investigated for the selection. There are various methods in human subjective approaches. Part 2 assumes that studies experimented with ATCos to identify their actions in simulated environments could reflect their strategies more than other approaches. Lastly, models from well known and more referenced studies are prioritized than others, which considers their fame reflects the overall quality of the models.

5.2 Model Transformation

Besides a fidelity of an existing prediction model, how a model is transformed affects its performance. The applied transformation method starts with mapping the model. Formats of the models vary, but essential information can be extracted. The transformation utilizes the extracted information for constructing computer programs for each portion of a model separately. Individual components of the transformed models connected to function as one after the parts were programmed.

The transformation of input for the selected model requires three processes. First of all, components of the model must be mapped. The models take different formats. For example, some models are descriptive, while others are constructed in the form of flow charts. The extraction of essential components for input, process, and output of a model is needed to unify the format. After the extraction, the method maps them to reproduce the model. After the mapping not only information to provide as an input, other additional information from other parts of the model can be identified. The identified information is listed to obtained from the collected data. Some of the listed information can be directly taken from the data, but others require calculations. This type of information includes differences between the status of paired aircraft or operational information such as the proximity of an aircraft to its destination.

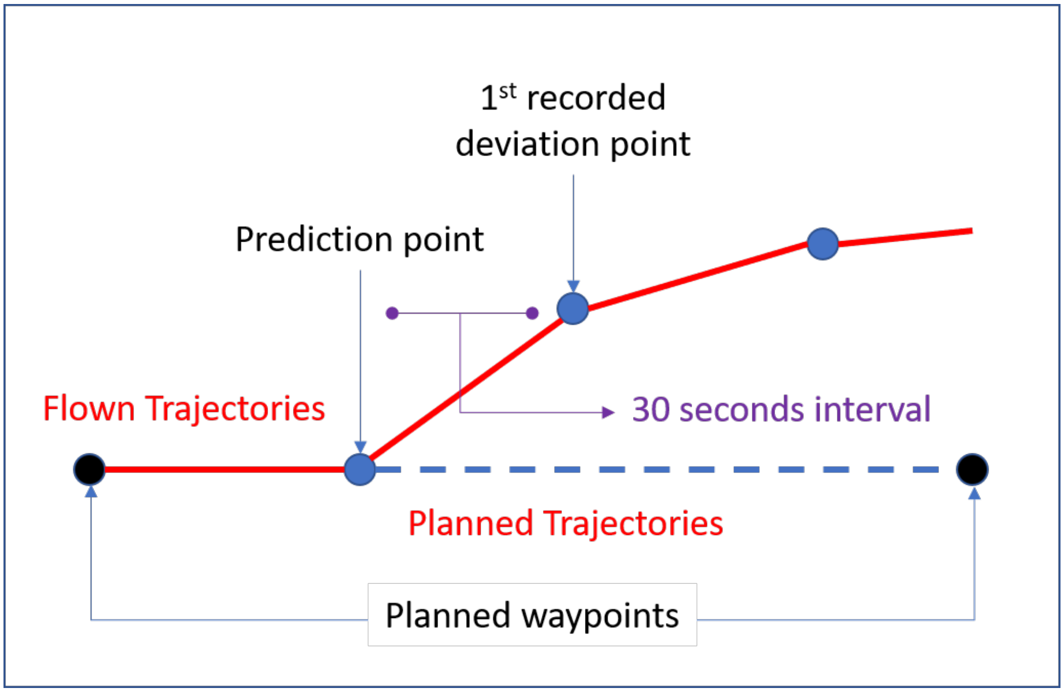


Figure 5.1.: A visual example of the deviation and prediction points

After deciding how to obtain the information, the method makes a decision on where to obtain the information from the collected data. Part 1 collected predicted aircraft conflicts from the process of identifying ATCo action from flight tracking data. Flown trajectories from closed-loop data that deviated from its flight plan in open-loop data are called deviation point, as shown in Figure 5.1. The point where a deviated aircraft initiated its deviation is called the deviation point. The actual deviation of the aircraft occurred somewhere between the deviation point and its previous one. Also, the corresponding ACTo's action delivered to the target aircraft should have occurred before the deviation point. There are approximately 30 seconds between the deviation point and its previous one. This method takes a conservative approach and considers the previous point as to where the deviated aircraft took the corresponding action. This point is called a prediction point. Information from the prediction points of the deviated aircraft is utilized for the input of the deviated aircraft. Aircraft from the conflicting pair that did not deviate does have the deviation point so that the discussed assumption cannot be applied. Figure 5.2 shows a method to assign a prediction point to the aircraft. The method assumes information of the non-deviated aircraft from the conflict pair when they were positioned at the same time as the prediction points of a deviated aircraft was at its prediction point. It takes a timestamp of the prediction points of the deviated aircraft from its closed-loop data and compares it with all timestamps of its counterpart to find one with the minimum differences.

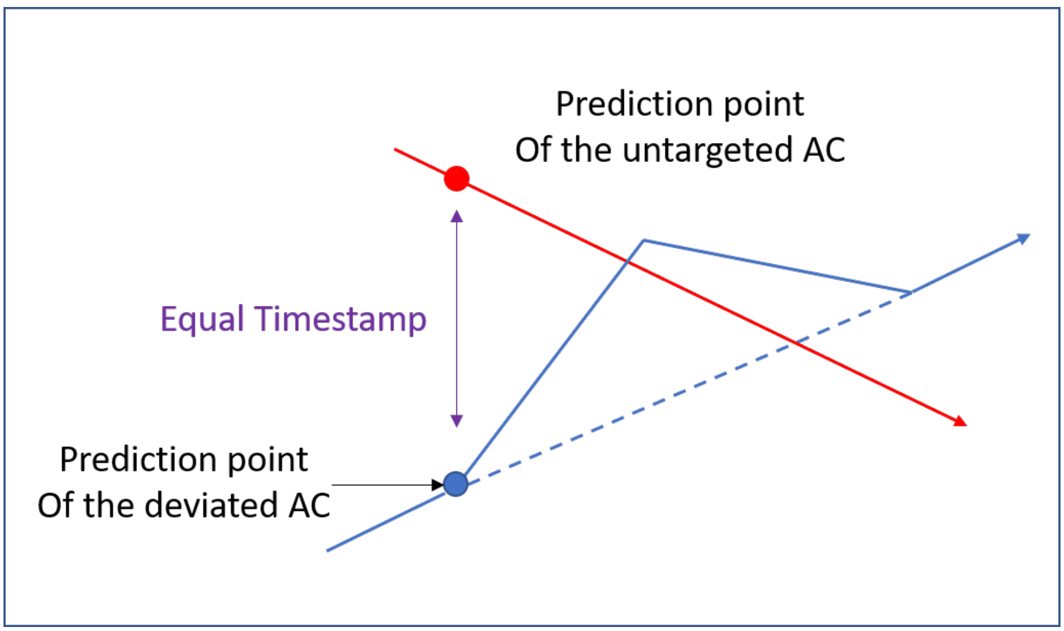


Figure 5.2.: A visual example of the prediction point of non-deviated aircraft

Transforming the solution generation process of a model is about building a hierarchical structure that takes input information from top and output solutions at the bottom. Mapped information from the input transformation applied again to understand how to input information is processed to generate solutions. Before the transformation, the method generates a network of the mapped information. Its nodes represent information processors, and edges represent the flow of information. Each node has two outgoing edges: one corresponds to the following processor and another one for terminating the solution generation process due to failure to satisfy conditions. Figure 5.3 illustrates the transformation of the solution generation process. The method builds if-statements out of each processor from the network to transform the solution generation process. It checks whether a processor requires multiple types of information to generate a decision and build if-statements for each type of information. For example, if a processor is "target a slower aircraft," there is only one statement to find which aircraft is slower. If a processor is "target a slower aircraft with lower altitude," then the method separates it into two statements: one for the speed and another one for the altitude. Second, the method checks the relationship between statements in a processor. The purpose of defining their relationship is to decide which outgoing edge that an outcome should take. If there are multiple statements in a processor, it can output two to the power of the number of the statements. In this example, there are four possible outcomes from the processor. Depends on the number of the statements, a set of other statements must be generated to decide which type of outcomes proceeds to the next processor and others to be terminated. The transformation process iterates the discussed process until it transforms all nodes in the network.

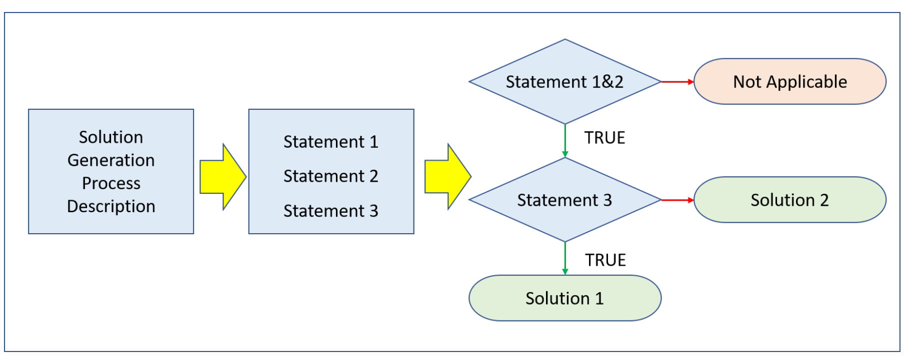


Figure 5.3.: An illustration of the model transformation process

The method transforms the generated model solution into two different forms. The first form is for the qualitative comparison. Part 1 sorted collected ATCo actions with three categories: target, type, and option. Identical categorization method is applied to model solutions. The second form is generating solution trajectories for the quantitative comparison. If a model provides specific guidelines, the method directly generates trajectories accordingly from the prediction point of a model solution's target aircraft. In other cases, a developed simulation generates trajectories to maintain minimum separation at the corresponding conflict point. The trajectory generation has three parts. Figure 5.4 illustrate the process. The first parts identify a point in airspace that resolves the corresponding aircraft conflict if the target aircraft deviates from its original route to head to the point and passing it. A simulation places a cylinder that represents minimum separation distances in the three-dimensional space centering at the conflict point. The dimension of the cylinder is five nautical miles wide from the center point and twenty flight levels above and below the point. The next step finds a point on the surface of the cylinder. A point on its surface meets the minimum requirements to resolve the corresponding conflict. The location of the point depends on a maneuver used in the model solution. After this point is decided, a simulation connects the point to the prediction point. A segment created by these two points becomes the first half of the solution trajectory. The second half is from the surface point back to the original route. Lastly, a simulation dissects the segment by every 30 seconds interval than fills dimensional information and expected arrival time for each point accordingly. Details of the output transformation further discussed in the results based on the selected model.

5.3 Qualitative Comparison

Qualitative comparison measures categorical differences between ATCo actions and model solutions on corresponding predicted aircraft conflict pairs collected from Part 1. The transformed model generates its solution in terms of the ATCo action

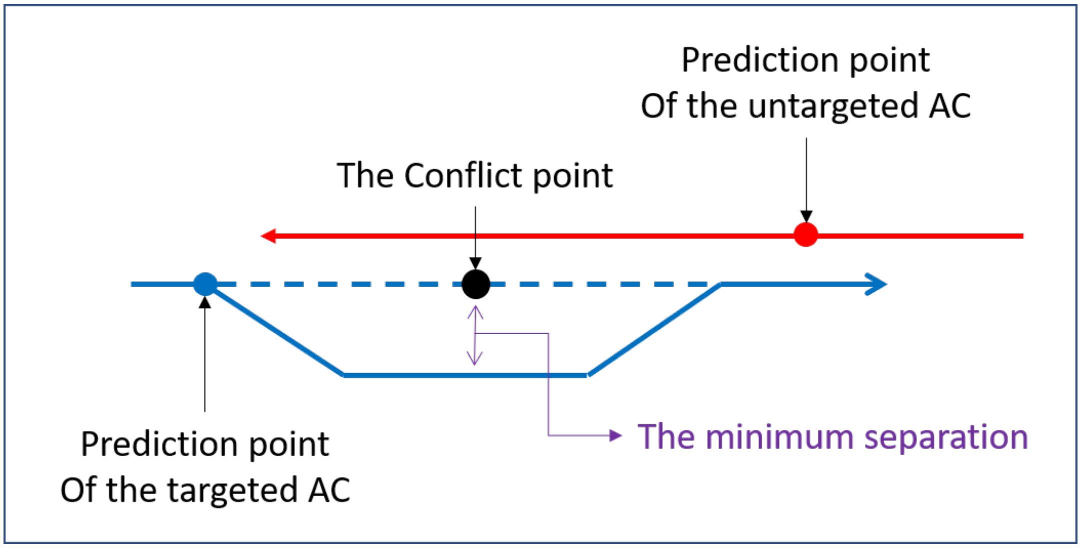


Figure 5.4.: A visual example of the minimum distance trajectory calculation

categorization method applied for Part 1. The comparison investigates differences in target, type, and option. If the selected model does not provide clear guidance on the option, the comparison is conducted on target and type. Figure 5.5 illustrates a form of results from the qualitative comparison. Within the collected predicted aircraft conflicts, the selected model can provide solutions. The model may not fully cover the conflicts due to its characteristics. Within the space that the model can be applied, there will be two major portions: one for having identical or similar solutions for the corresponding ATCo actions and another that are different. The Identical solutions are ones having identical targets and maneuvers. However, similar solutions are ones with identical maneuvers but the different target. The different solutions are having either identical targets, but different maneuvers or both targets and maneuvers are different. Equivalent in maneuver is weighted more than the selected target aircraft because it is the actual method taken to resolve the corresponding conflict. Also, it is possible to apply a maneuver with the identical type but different options and details to the different target. For example, if a conflict can be resolved by moving one aircraft to a higher altitude, ideally the same type of maneuver but lowering the altitude of another aircraft could resolve the conflict too. Thus, having a difference only on the target is considered a similar solution.

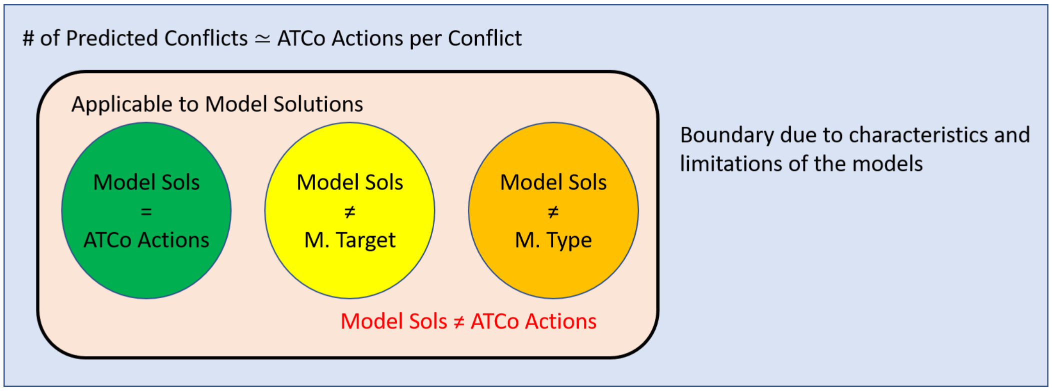


Figure 5.5.: An illustration of the result from qualitative comparison

5.4 Feature Comparison

Feature comparison investigates differences among the grouped solutions from the Qualitative comparison. More specifically, the comparison method investigates differences from the identical group resulted from the qualitative comparison to other groups. The comparison conducts series of clustering analysis between the sub-groups. Binomial classification tree was applied for the analysis. The modeling method is based on Breiman et.al (1984) [42]. The analysis takes binomial form by assigning one sub-group's response variables assigned as positive (one) and another sub-group as negative (zero). For the analysis, all collected data responses to each sub-group are taken as input variables. Tree plots for each comparison were conducted to show how each explanatory variable affect the clustering. Tree pruning technique is applied to avoid overfitting. The cross validation was applied for the pruning. The technique selects a size of tree based on the original tree that minimizes the cross validated error by computing the minimum complexity parameter.

Table 5.1 shows a list of the flight contextual information extracted from the collected data. Flight contextual information is defined as information that describes both physical and operational information of an aircraft during its operation. For example, the location and speed of aircraft correspond to physical information, while its departure and arrival are operational information. Flight contextual information is part of flight data. Its portion is shared with flight tracking data (open and closed-loop data of aircraft) and air traffic data (operational information about air traffic control systems as airspace information). Part 1 collected flight tracking data and some portion of traffic data related to it. Thus, applied flight contextual information is extracted from both flight tracking data and air traffic data, which is not a comprehensive list of it.

The extraction of the flight contextual information is based on three states of each aircraft: prediction, deviation, and conflict points. The point where an aircraft deviated from its planned route to avoid a predicted aircraft conflict is called a deviation point. Since the closed-loop data were collected approximately every thirty seconds, the actual deviation of the aircraft occurred somewhere between the deviation point and its previous one. Also, the corresponding ACTo's action delivered to the target aircraft should have occurred before the deviation point. This method takes a conservative approach and considers the previous point as to where the deviated aircraft took the corresponding action. This point is called a prediction point. Lastly, a conflict point is a location on the original route of an aircraft, where it is predicted to have a conflict with another aircraft.

Three different extraction methods were applied to obtain the listed information. The first type of contextual information is directly given by flight tracking data. Altitudes and ground speeds of aircraft at their prediction points are included in the closed-loop data. Ground speed is a summation of airspeed, actual speed generated by an aircraft, and wind speed. It does not use airspeed since it was not given by the data and the wind speed at the moment is unknown. Both variables continuous variables from zero to infinite and both aircraft in a conflict pair have their variables. The second type of information is the variables generated by computing flight tracking data. Distance and heading calculations belong to this group. Geodesic was applied to calculated distances among three different locations: the prediction to the conflict points, the conflict to the destination points, and the prediction to the destination points. They are continuous variables ranging from zero to infinite, and there are variables for each aircraft in a conflict pair. Heading angles were calculated based on the projection angle between two points. The angle can be a relative value, so bearing was applied to standardize it. There are three angular variables for each aircraft, and they are categorical. Instead of precise degrees, a degree from zero to three hundred and sixty was separated into eight pieces in a clockwise direction. Each section is forty-five degrees wide, starting from zero degrees. The operational phase of aircraft presents a stage of an aircraft from its operations. There are five main stages in a flight operation: departing, ascending, cruising, descending, and landing. Part 3 utilizes stages from ascending to descending since departing and landing stages are not responsible for the targeted ATCos for high-altitude airspace sectors. The method added intermediate stages in-between the three phases as a preparation phase to shift the stage of flight operations. These intermediates are right before and after aircraft enter or leave high-altitude sectors. Variables for the operational phases are categorical. Each aircraft has one for their prediction and conflict points because their operation phase can be different at those points, and it can affect ATCo actions. Another indicator for the operation phase is included to show whether aircraft change its phase if it is at their conflict points at the point of prediction point. The last type of flight contextual information results from computing flight tacking data with air traffic data. Unlike other variables that each aircraft has their own, there is one only categorical variable for the corresponding airspace for the conflict pairs because both aircraft are always in the same airspace at their prediction points. Airspace information is generated by comparing boundary coordinates of targeted aircraft and locational information in the closed-loop data to check whether an aircraft is inside the boundaries at its prediction point. There are three categories for the variables, which indicate three airspaces where the flight tracking data was collected. Traffic information is a special form of this type. In air traffic control systems, traffic is defined as the number of aircraft in a sector. An airspace sector is the smallest unit of airspace that an ATCo manages its traffic. Sector information can be found from the airspace map, but the coordinates are unknown. Arbitrary sectors were developed based on the information gained from the map. From the map, the area of the sectors in the targeted airspace can be measured. The size of the arbitrary sectors is set to be equivalent to the average of actual sectors' sizes. The average is a hundred square nautical mile square. The arbitrary sectors are shaped in squares, and its center is located on the prediction points. Calculation of the traffic counts aircraft that passed the arbitrary sector and checks whether their operation times is within five minutes from the timestamps of the prediction points. There is one traffic variable for both aircraft in a pair, and it is categorized into three levels: low, medium, and high, based on statistical analysis on the calculated variables for all conflict pairs.

5.5 Quantitative Comparison

Quantitative comparison investigates whether model solutions can be applied to the aircraft conflicts with ATCo actions categorically different from the solutions. From the qualitative comparison, three different groups of the model solutions are identified. The quantitative comparison focused on the groups with differences in maneuvers. It does not check applicability on the group of aircraft conflicts that cannot take model solutions because they are outside of the solution boundary for the selected model. The comparison measures three different aspects of applicability. First, it checks whether there are any operational limitations to apply the model solutions to aircraft conflicts. Situations including one or both aircraft either ascending or descending at their prediction points fall into this case. The second measurement checks the conflicts that qualify from the first measurement. It calculates whether the target aircraft from the corresponding model solution has enough distance from its conflict point to take the solution maneuver and safely avoid its predicted conflict.

The secured distance for a deviation is measured based on the type of model solution and further discussed from the result with the selected model.

The last measurement checks to the solutions satisfy the first two measurements to check the occurrence of secondary conflicts. A secondary conflict is a conflict between a deviated aircraft and other aircraft that are not the counterpart of the deviated aircraft. It is possible to cause another problem if a maneuver that is different from the corresponding ATCo action was applied. Based on the collected information from Part 1, the only problem that this study can detect is the secondary conflict. Detection of the secondary conflict utilizes the method used for detection Atco actions and the corresponding predicted aircraft conflicts from Part 1. Like the aircraft conflict pair detection algorithm of Part 1, the secondary conflict detection algorithm takes a deviated region of the model solution to predict conflict. The algorithm finds any other aircraft that passed the boxed deviated area to check the lateral separation first. The box is generated by the maximum and minimum values of longitudes and latitudes from the closed-loop coordinates that correspond to the deviated region. After the box is generated, the algorithm stretches the box by 1 degree from both latitudes and longitudes on both sides. The stretching is a technique to widen the searching area. It is critical in a case where the deviated region is relatively small or narrow. The algorithm checks how close the other aircraft is to the deviated one. The distance calculation from the deviation detection was adapted for the calculation. The algorithm calculates the shortest distance between open-loop coordinates of the deviated aircraft and closed-loop coordinates of the second aircraft within the box. In lateral deviation, a deviated aircraft will no longer have a lateral separation violation. It is expected to fly on the planned route, so the closed-loop coordinates are on those of open-loop. In a vertical violation, both aircraft also must violate lateral separation. For the speed, the violation can be either one. After calculating the shortest distances between them, the algorithm checks whether the distance violates a lateral separation. If it does violate the rule, the open-loop position of the deviated aircraft and closed-loop position of the second aircraft is considered as conflict points. If the distance does not violate the rule, the second aircraft was not considered for a conflict pair. Lastly, the algorithm calculates arrival time to the conflict points. The second aircraft directly use its corresponding timestamp from its closed-loop data. For the deviated aircraft, both vertical and speed deviations directly use corresponding timestamps. In the case of the lateral deviation, the algorithm takes the timestamp of closed-loop data. It takes timestamp from the deviated points that are perpendicular to its conflict point as predicted arrival time. The algorithm calculates the difference between the two arrival times. If the difference is less than 5 minutes, the corresponding aircraft is considered as a predicted secondary conflict pair.

Table 5.1.: The list of flight contextual information

<table>
<tr><th>Variable</th><th>Notation</th><th>Variable Type</th><th>Range</th><th>Unit</th><th>AC1&2</th><th>Context</th></tr>
<tr><td>Altitude at the predicted point</td><td>Ae</td><td>Cont.</td><td>5 - 450</td><td>FL</td><td>Y</td><td>Actual altitude</td></tr>
<tr><td>Ground speed at a prediction</td><td>Se</td><td>Cont.</td><td>130 - 644</td><td>kt</td><td>Y</td><td>Leveled ground speed</td></tr>
<tr><td>Distance from a prediction to a conflict point</td><td>Dec</td><td>Cont.</td><td>0 - 3684</td><td rowspan="3">km</td><td>Y</td><td rowspan="3">Geodesic between coordinates</td></tr>
<tr><td>Distance from a prediction to a destination</td><td>Ded</td><td>Cont.</td><td>113 - 2204</td><td>Y</td></tr>
<tr><td>Distance from a conflict to a destination</td><td>Dcd</td><td>Cont.</td><td>78 - 1799</td><td>Y</td></tr>
<tr><td>Heading angle from a prediction to a conflict</td><td>Bec</td><td>Cat.</td><td>1 - 8</td><td rowspan="8">NA</td><td>Y</td><td rowspan="3">Dividing bearing into 8 pieces
with interval of 45 degrees from 0 degree</td></tr>
<tr><td>Heading angle from a prediction to a destination</td><td>Bed</td><td>Cat.</td><td>1 - 8</td><td>Y</td></tr>
<tr><td>Heading angle from a conflict to a destination</td><td>Bec</td><td>Cat.</td><td>1 - 8</td><td>Y</td></tr>
<tr><td>Operation phase at a prediction</td><td>Pe</td><td>Cat.</td><td>1 - 5</td><td>Y</td><td rowspan="2">5 phases from ascending to descending
in sequential order</td></tr>
<tr><td>Operation phase at a conflict</td><td>Pc</td><td>Cat.</td><td>1 - 5</td><td>Y</td></tr>
<tr><td>Operation phase change from a prediction to a conflict</td><td>Ps</td><td>Cat.</td><td>0 & 1</td><td>Y</td><td>0: False, 1: True</td></tr>
<tr><td>Air space sector traffic at a prediction</td><td>T</td><td>Cat.</td><td>1 - 3</td><td>N</td><td>Arbitrary sector</td></tr>
<tr><td>Airspace</td><td>S</td><td>Cat.</td><td>1 - 3</td><td>N</td><td>1: ZLA, 2: ZOB, and 3: ZTL</td></tr>
</table>

6. PART 2: RESULTS

6.1 Model Selection

A prediction model called best practice was selected. Many models are targeting en-routing aircraft based on human subjective studies. However, the models did not qualify the major conditions, mostly due to being unable to transform them. Those models did not specify target aircraft, details for the deviations, or both. Other candidates satisfied the major conditions, but only the best practice satisfied the conditions for the following reasons. First, the method can generate qualitative and quantitative solutions based on the given descriptions from the literature. Also, all required input data can be retrieved from the collected data. Third, the method provides clear guidance to process input data to generate solutions. Two other candidates also satisfy the discussed conditions. One of them was not selected because the model only deals with an operational situation that aircraft are preparing for descending while they are in high-altitude sectors. Another model was excluded because even though it can generate more various solutions. It was based on European air traffic, while the selected model resulted from studying US ATCos. The method assumes that regional characteristics exist and reflected in the ATCo actions. Thus, models based on a specific region cannot be compared against ATCo actions from a different region. Lastly, the purpose of this work is to develop an evaluation method for the existing prediction models against actual ATCo action. Thus, the decision was made to focus on the quality of the evaluation rather than input quantity.

The best practice is a set of strategies that expert ATCos tend to apply to predicted aircraft conflict pairs [15,16,20,32,34,43,44]. The main strategy is placing one aircraft behind another to minimize workload coming from continuous monitoring. The strategies can set the aircraft and may not require further attention and actions.

Existing prediction models were found by searching them with related keywords and reviewed with the conditions. The model satisfies the significant conditions. The best practice is based on human subjective studies. It is designed for aircraft conflict pairs by en-routing aircraft in high-altitude sectors. The model generated nine different conflict resolutions based on the physical and operational status of aircraft when ATCos detected the conflicts. It makes decisions based on speed, proximity to their conflict points, and the angle between the aircraft to decide which model solution to apply. Among the nine possible solutions, three of them are vague on the target to deviate from its original route. Also, the model generates lateral deviations only.

6.2 Model Transformation

Figure 6.1 illustrated the transformed model. The selected existing prediction model was separated into three parts: input, process, and output. As input, the model requires an angle between the pair of aircraft. Depends on the angles, the model separates the aircraft conflicts into five cases. The angle was generated by calculating the bearing between the heading angle of two aircraft at their prediction points. Heading angle was calculated by projecting a bearing from a point before a conflict point to it. Processors of the selected model require the current speed of aircraft and distances from the prediction points to the conflict points. The processors utilize the information to decide the targets and solutions. The recorded speed at the prediction points is retrieved, and the distances were calculated based on geodesic between the prediction and conflict points. The output of the selected model was transformed into two forms: qualitative and quantitative solutions. The qualitative solutions follow the ATCo categorization method. The selected model only generates lateral maneuvers, so the type layer from the categorization is fixed. Also, the model did not specify the option, and the option layer was not considered. The selected target from the prediction model was reinterpreted in terms of the target categorization that is defined by distances to their conflict points.

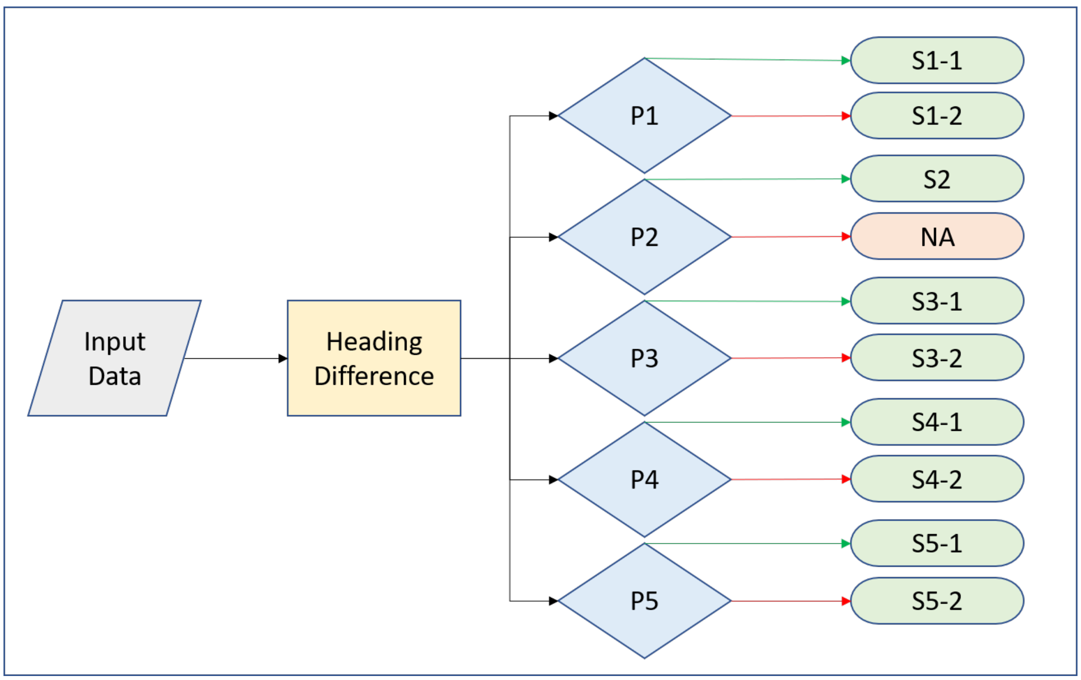


Figure 6.1.: An illustration of the selected model

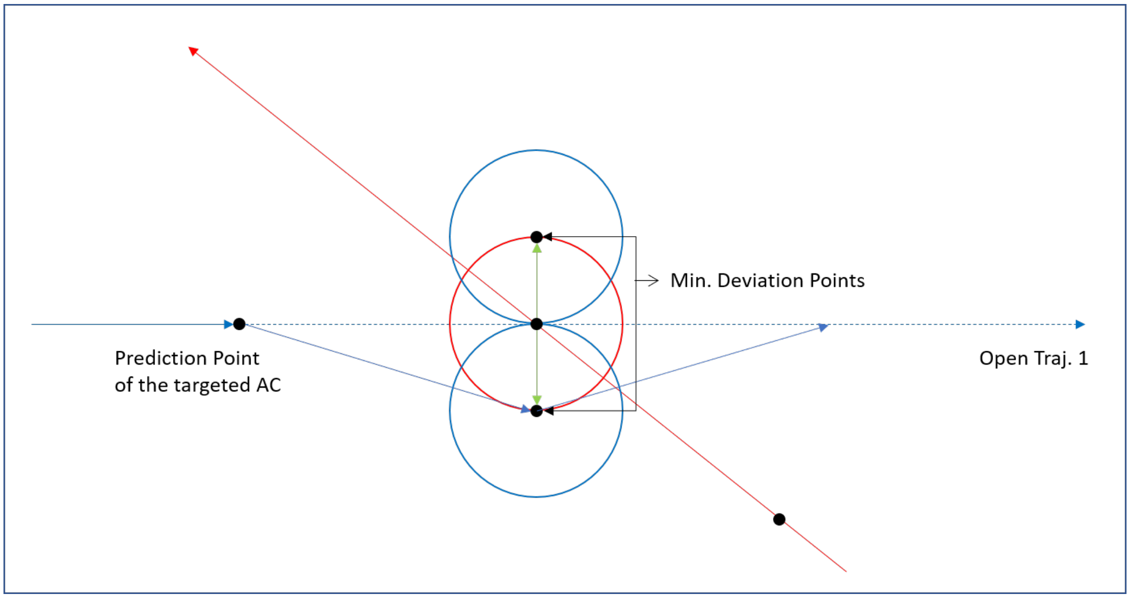


Figure 6.2.: An illustration of the quantitative solution generation process

The quantitative model solution generates trajectories that deviate the target aircraft laterally from its prediction points. The output of the selected model guide how to put the selected aircraft behind another one. The solution first locates the point that resolves the predicted conflict by the minimum separation distance at the conflict point. Figure 6.2 illustrates the process. It generates two points that are perpendicular to a conflict point and distanced five nautical miles away from it. Based on the angle between a pair of aircraft, the quantitative solution finds a point that will put the deviated aircraft behind another one. The rest of the process to generate trajectories follows processes introduced from Part 2: Methods.

6.3 Qualitative Comparison

The qualitative comparison measures difference between the model solutions and actual ATCo actions from the same predicted aircraft conflict pairs in terms of the categorization method developed for analyzing the collected ATCo actions. Figure 6.3 shows the results of the individual conflicts from the collected ATCo actions. Among

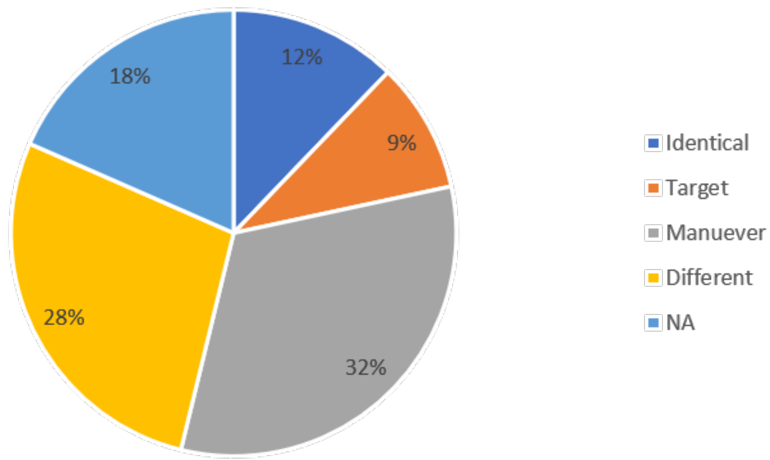


Figure 6.3.: An overview of the qualitative comparison on individual aircraft conflicts

1,312 maneuvers, the selected model can generate solutions on eighty-two percent (1,081 conflicts) of them. The non-applicable maneuvers are due to unclear solutions to specific cases. Twenty-one percent (284 conflicts) results in their ATCo actions are either identical or similar to the corresponding model solutions. The last sixty percent (786 conflicts) of the maneuvers are having different results between the model solutions and the ATCo actions. From the identical and similar group, twelve percent (160 conflicts) are identical, while another nine percent is having a difference in the target selection, but the maneuvers are identical. Among the different groups, thirty-two percent (422 conflicts) is having an identical target but different maneuvers. The last twenty-eight percent (364 conflicts) have different target aircraft and different maneuvers.

Figure 6.4 shows the qualitative comparison of the collected individual maneuvers by each airspace. The results show a similar trend as Figure 6.3. The proportion of the applicable sets is about 80 percent. Both ZLA and ZOB has slightly higher numbers (eighty-four percent) than ZTL (seventy-nine percent). The proportions

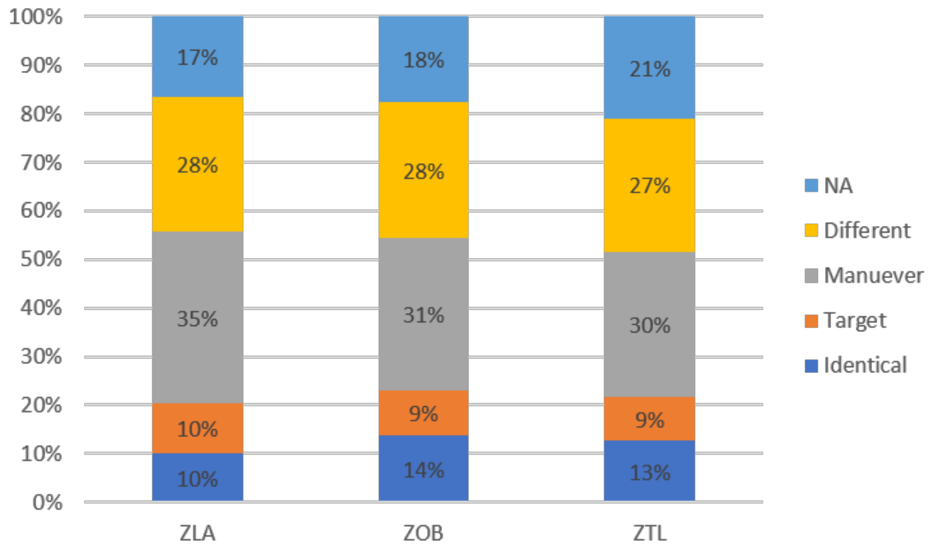


Figure 6.4.: An overview of the qualitative comparison on individual aircraft conflicts by each airspace

of the identical groups are at least ten percent across the airspaces. That of ZOB (fourteen percent) is slightly higher than the others. The proportions of similar groups are similar. The group with different targets from ZLA has the highest proportion (thirty-five percent) among all. Lastly, the proportions of the groups with differences in both target and maneuver are approximately similar among the airspaces.

Figure 6.5 shows the qualitative comparison of the predicted aircraft conflicts with single maneuvers. The selected model can generate solutions to slightly less than eighty percent (306 conflicts) of the conflicts from a total of 398 conflicts. Like the results above, about ten percent (44 conflicts) of the conflicts have identical model solutions and ATCo actions. Nine percent (36 conflicts) of the conflicts have a difference in the selected target. Twenty-six percent (104 conflicts) of conflicts have identical targets between their model solutions and ATCo actions, but the applied maneuvers are different. The last twenty-nine percent (114 conflicts) have differences in both targets and maneuvers.

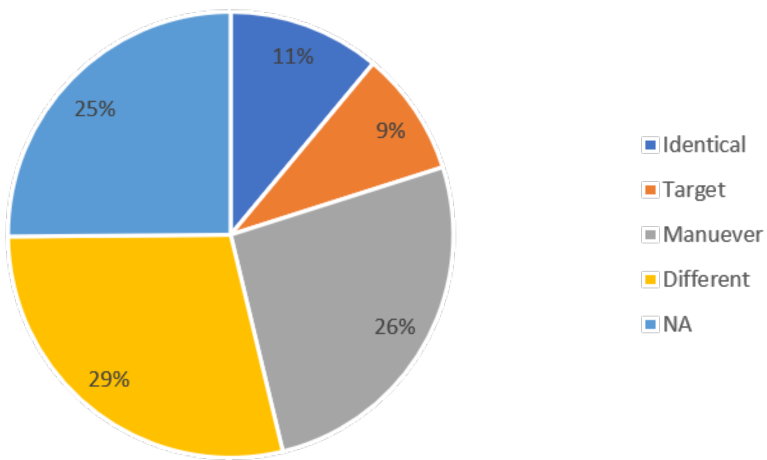


Figure 6.5.: An overview of the qualitative comparison on single-maneuver aircraft conflicts

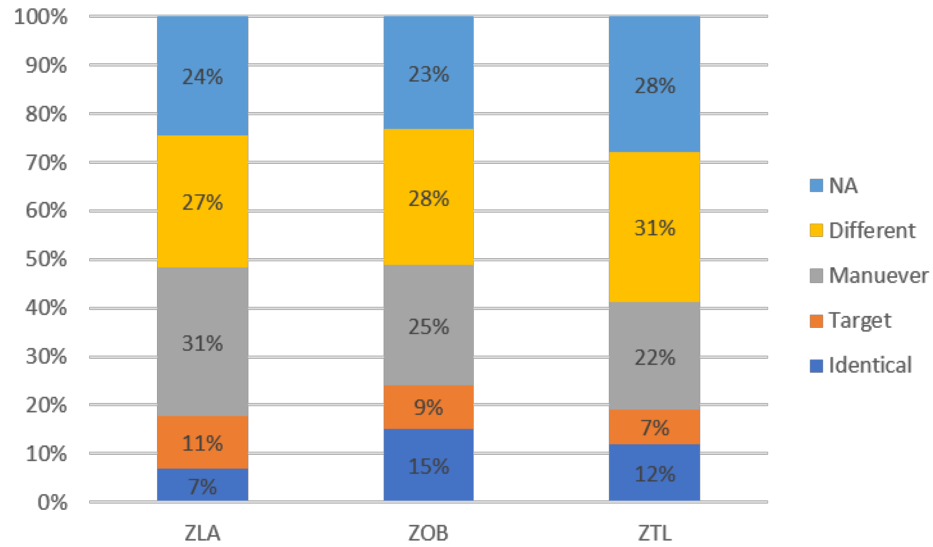


Figure 6.6.: An overview of the qualitative comparison on single-maneuver aircraft conflicts by each airspace

Figure 6.6 shows the results of each airspace. Results on each airspace show slight differences, but significant trends in the proportions are the same. Unlike the comparison on the individual conflicts, the proportions of the applicable sets are slightly lower except for ZOB (eighty-one percent). However, those of the identical groups are higher except for ZLA (seven percent). ZLA has the highest proportion of the group with a different target (eleven percent), while others are below ten percent. Also, ZLA shows a significantly high proportion (31 percent) on the group with identical targets but different maneuvers. Lastly, the proportions of the group with the different targets and maneuvers are similar across the airspaces.

6.4 Feature Comparison

Figure 6.7 shows the tree graph of the feature comparison between the identical group and the group with different targets. The first node of the tree is the altitude of aircraft that was not selected by ATCo. If the altitude is below 107 FL, there is a high

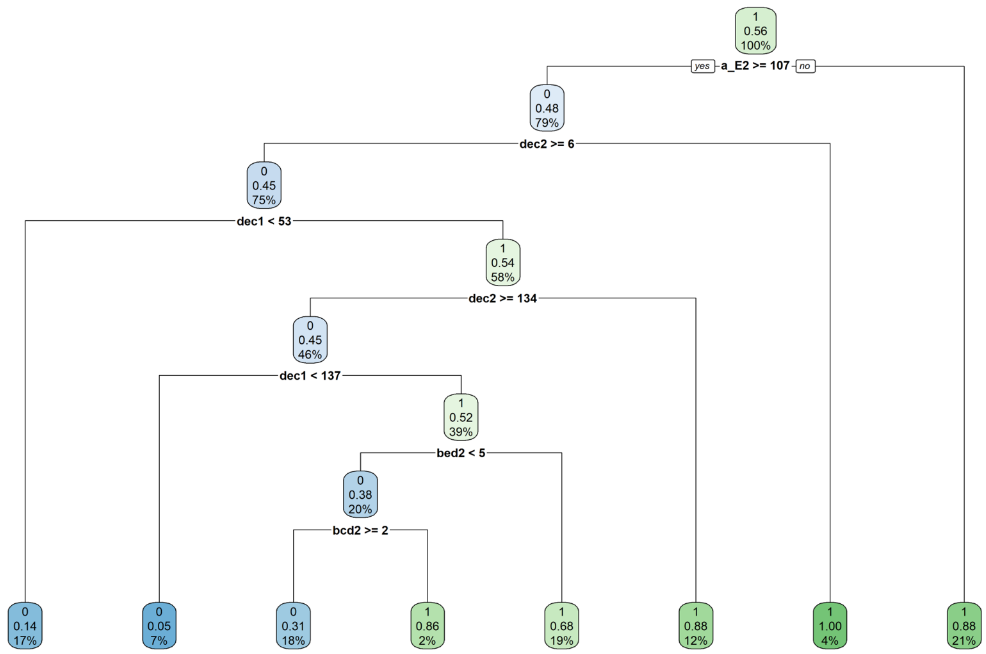


Figure 6.7.: A tree graph of the identical group vs. the target group

probability that a model solution is identical to ATCo actions on the corresponding aircraft conflict. The altitude parameter at the prediction point implies that the aircraft is ascending. IT can be interpreted as if the untargeted aircraft is not in such condition, ATCo may apply the maneuver to it. Following list shows the influential flight contextual information that explains the relationship between the groups among 24 variables. The complete list of the table is in Appendix.

- Distance from the prediction to the conflict point of the untargeted aircraft: 20%
- Speed of aircraft at the prediction point of the untargeted aircraft: 17%
- Distance from the prediction to the conflict point of the targeted aircraft: 15%
- Altitude at the prediction point of untargeted aircraft: 14%

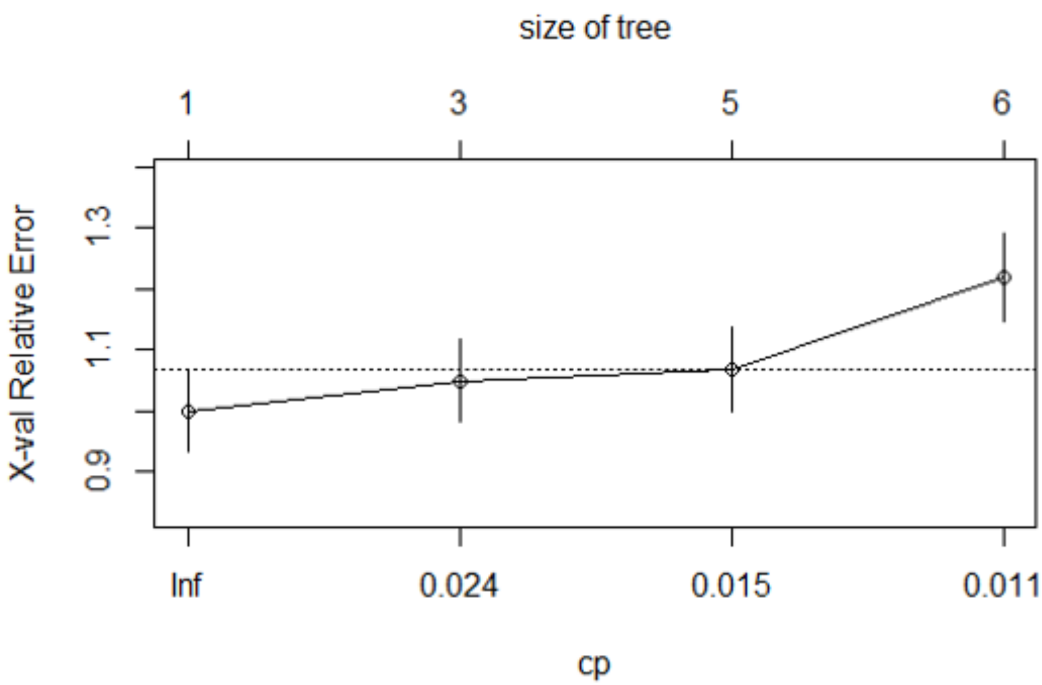


Figure 6.8.: A cross-validation graph of the identical group vs. the maneuver group

Figure 6.8 shows the cross-validation results of the comparison between the identical group and group with identical targets but different maneuvers. The graph shows that the first node of the tree has the lowest complexity parameter. Also, relative error (root mean square error) does not improve as the node continues. It implies that the clustering method failed to find explanatory variables to explain the difference between the groups. It can be interpreted as the applied flight contextual information was not comprehensive enough for explain the difference between the groups.

Figure 6.9 shows the tree graph of the feature comparison between the identical groups and the group with different targets and maneuvers. Like the comparison between the identical groups and the group with different targets, the applied classification tree selected altitude at the prediction point of the untargeted aircraft by ATCos as the first variable to cluster the results. The parameter of the variable also indicates whether the untargeted aircraft by ATCos are in ascending phases. These two results imply that the processes of the selected prediction model eventually does

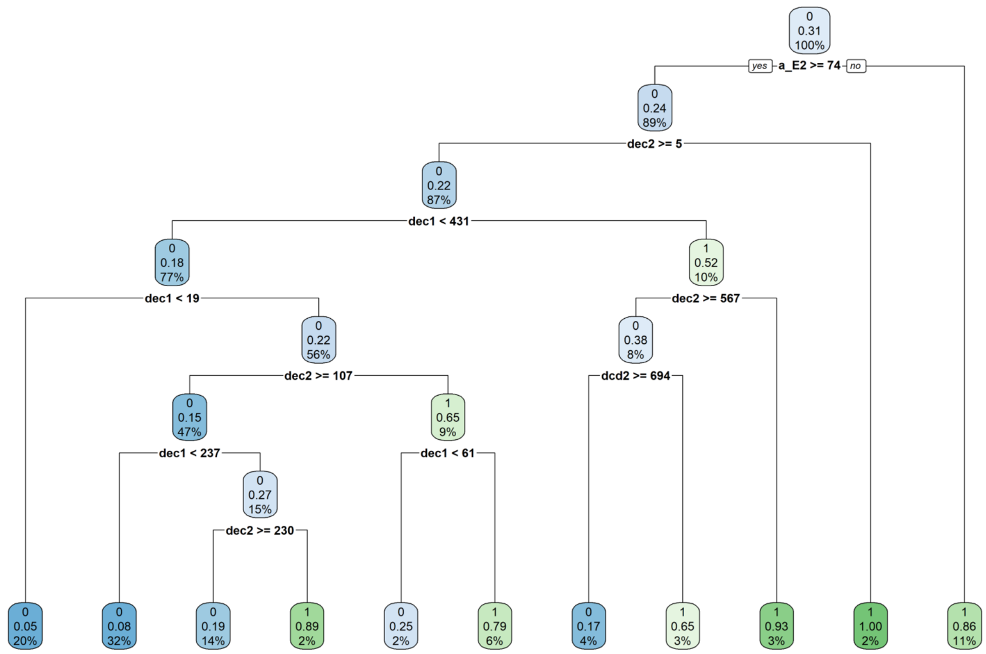


Figure 6.9.: A tree graph of the identical group vs. the different group

not select aircraft that is in critical conditions without direct consideration of them since its processes do not consider them. Following list shows the most influential flight contextual information. The list is identical to the list above but the order is slightly different.

- Distance between the prediction and conflict points of untargeted aircraft: 29%
- Altitude at the prediction point of untargeted aircraft: 19%
- Speed at the prediction point of untargeted aircraft: 19%
- Distance between the prediction and conflict points of targeted aircraft: 14%

6.5 Quantitative Comparison

The quantitative comparison checks whether the model solution can be applied to the broader range. The qualitative comparison found a group of conflicts having a difference between model solutions and ATCo actions in applied maneuvers or both targets and maneuvers. The quantitative comparison checks the applicability of the model solutions to this group. Figure 6.10 shows the results of the comparison of individual conflicts. Out of 786 individual conflicts, forty-one percent can take their model solutions. However, fifty percent (394 conflicts) cannot take the model solution due to at least one aircraft in a conflict pair is in critical condition at the point of prediction. The critical conditions include aircraft either ascending or descending. If an aircraft is in such a phase, ATCos tends not to apply an action to the aircraft unless there are no other options. Even the targeted aircraft are not in one of the conditions, it still limits possible options and resulting in putting the pair in a different situation compared to the pairs without those conditions. Five percent (39 conflicts) of the individual conflicts cannot take the model solutions because they cannot secure enough distance to deviate and ensure minimum distance at the conflict points. In other words, these aircraft are too close to their conflict points. Two percent (17 conflicts) cannot take the model solutions due to unable to secure distance to come back to the original route. Aircraft that are close to its descending phase corresponds to this portion. Their conflict points are close to the point where aircraft must start descending for preparing to land. Even if they can avoid the conflicts, the minimum distance required to come back is not secured since the aircraft must start descending and landing. Lastly, 1 percent (10 conflicts) cannot take the model solution due to secondary conflicts. The secondary conflict is a conflict caused by deviating aircraft to avoid its primary conflict.

Figure 6.11 shows the results of each airspace. Results from ZLA and ZTL shows similar results to the overall results. However, ZOB shows different results. Thirty-seven percent (95 conflicts) of the individual conflicts from ZOB can take their model

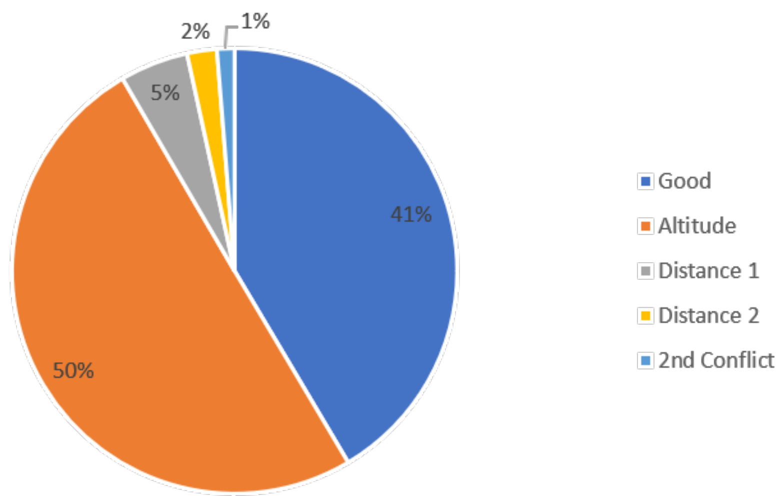


Figure 6.10.: An overview of the quantitative comparison on the individual aircraft conflicts

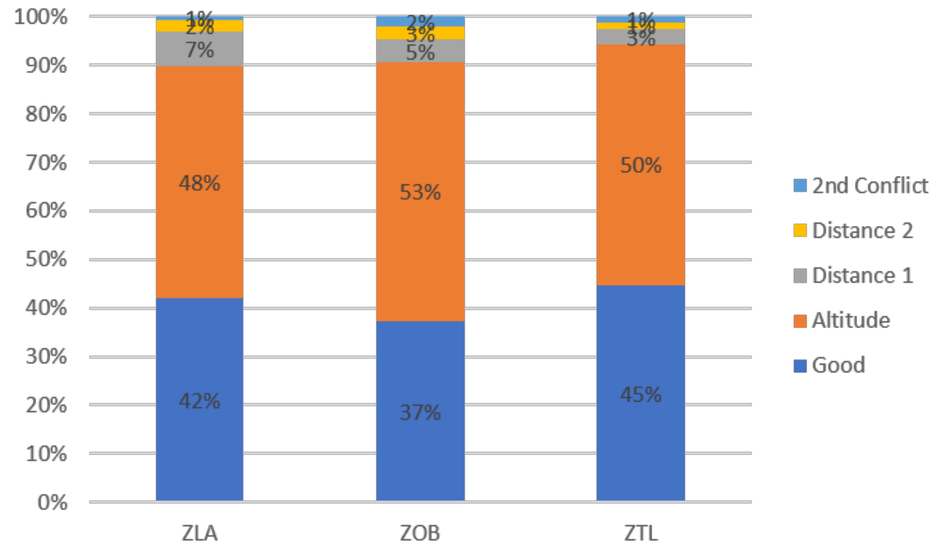


Figure 6.11.: An overview of the quantitative comparison on the individual aircraft conflicts by each airspace

solutions. Its proportion is about twenty percent less than those of the other two airspaces. Also, ZOB has the highest proportions of the conflicts excluded due to the critical conditions. The numbers of the conflicts causing secondary conflicts are similar across airspaces. The conflicts causing issues due to ensuring distanced to or from the conflict points show similar results. However, the total number of cases according to these categories is significantly lower than others. Thus, it is difficult to conclude from the comparison among the airspaces.

Figure 6.12 shows the results from the ATCo actions with single maneuvers. Out of 218 conflicts, forty-six percent (101 conflicts) of them are applicable without any issues. However, forty-two percent (92 conflicts) cannot take the model solutions due to aircraft in the conflict pairs are in critical condition. Also, eleven percent (24 conflicts) of the conflicts cannot take the model solutions due to failure to secure distance to or from the conflict points. There is only one conflict that causes a secondary conflict if the targeted aircraft takes its model solution. Figure 6.13 shows the results of each airspace. Like individual conflicts, ZOB has the lowest proportion

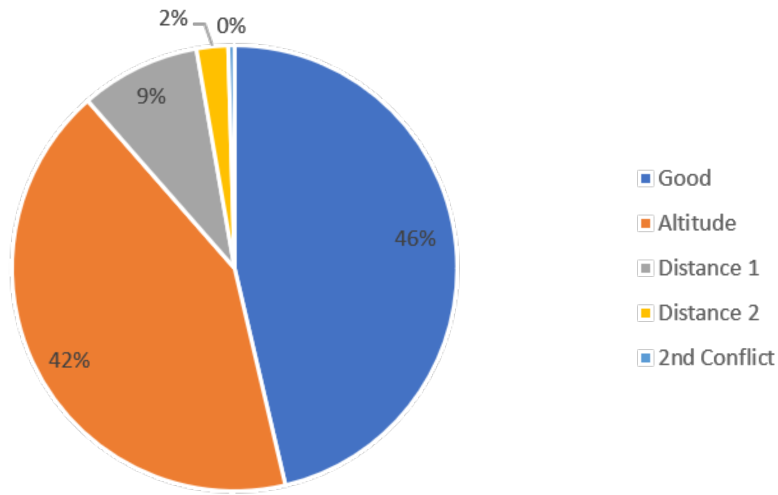


Figure 6.12.: An overview of the quantitative comparison on the single-maneuver aircraft conflicts

of the conflicts that can take their model solutions. Three airspaces result in about the same number of conflicts causing issues due to one aircraft in one of the critical conditions and issues in securing distance to the conflict points. Only ZTL has a conflict that causes the secondary conflict from its model solution. Also, ZTL does not have a conflict that has a distance issue coming back from its model solution. However, the total number of conflicts that correspond to the distance issues are very low to make conclusions.

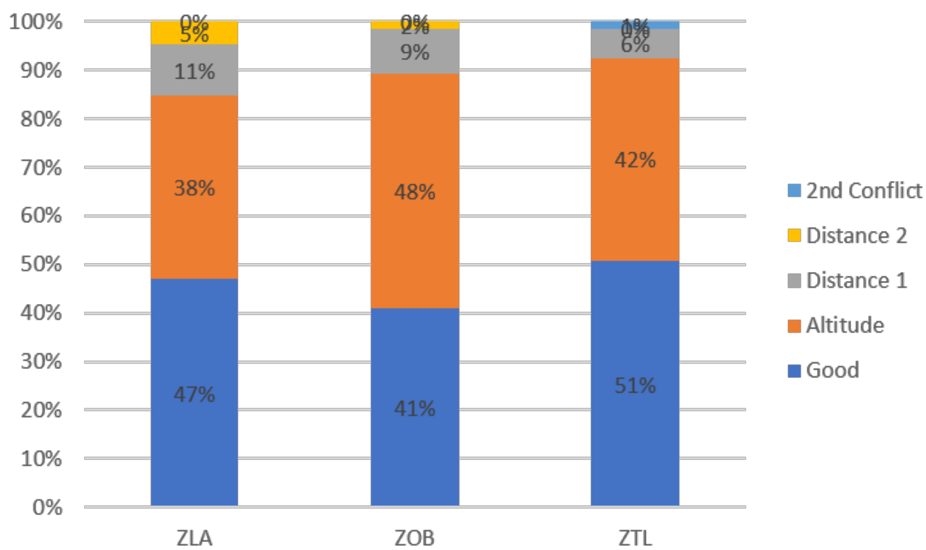


Figure 6.13.: An overview of the quantitative comparison on the single-maneuver aircraft conflicts by each airspace

7. PART 3: METHODS

The conventional studies on ATCo actions with human subjective approaches focused on the relationship between aircraft conflicts and ATCos. Researchers utilized knowledge gained to understand ATCo actions and developed prediction models. The studies were not directly focused on the ATCo actions but as a result of the interaction between air traffic and ATCos. Thus, we can conclude that the relationship between existing prediction models and ATCo actions are indirect. Unlike them, Part 3 developed a prediction model based on the direct relationship between ATCo actions and predicted aircraft conflict pairs. Part 3 generated flight contextual information to represent the predicted aircraft conflicts. This information is a list of variables that describes both operational and physical states of aircraft. This information was used as explanatory variables, while the collected ATCo actions from Part 1 as response variables. Part 3 developed a prediction model with a hierarchical structure of sub-models to reflect the structure of ATCo actions that were applied to categorize collected data from Part 1. Three different statistical prediction modeling methods were conducted as a method to investigate whether the contextual variables play different roles due to differences from the applied modeling method.

7.1 Flight Contextual Information

Flight contextual information is defined as information that describes both physical and operational information of an aircraft during its operation. For example, the location and speed of aircraft correspond to physical information, while its departure and arrival are operational information. Figure 7.1 illustrates the relationship between information within flight data, which is relevant to the topic. Flight contextual information is part of flight data. Its portion is shared with flight tracking data (open and closed-loop data of aircraft) and air traffic data (operational information about air traffic control systems as airspace information). Part 1 collected flight tracking data and some portion of traffic data related to it. Thus, applied flight contextual information is extracted from both flight tracking data and air traffic data, which is not a comprehensive list of it.

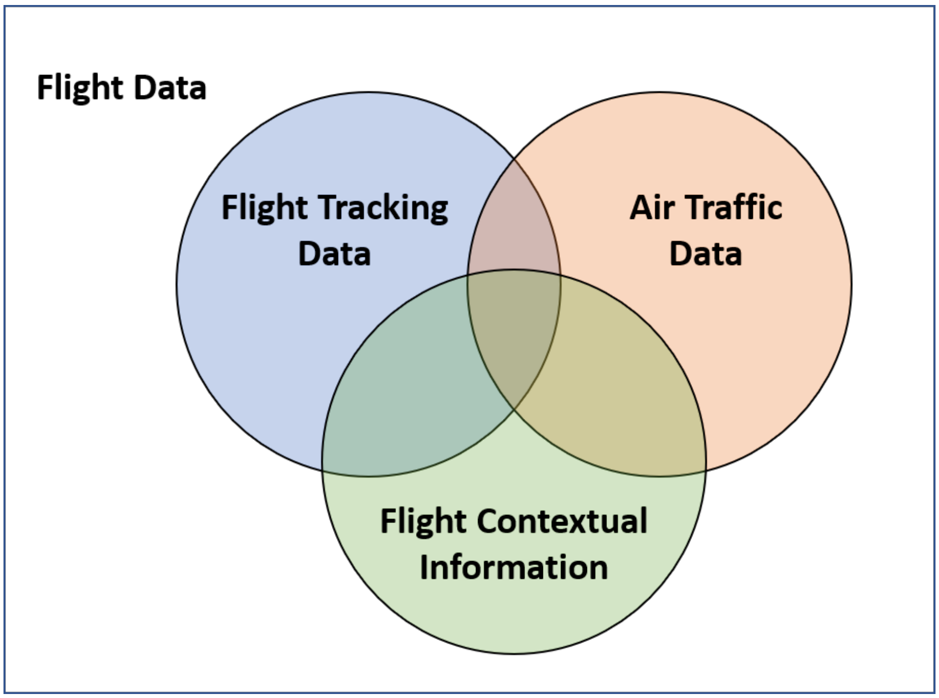


Figure 7.1.: An illustration of relationship among information in the flight data

The extraction of the flight contextual information is based on three states of each aircraft: prediction, deviation, and conflict points. The point where an aircraft deviated from its planned route to avoid a predicted aircraft conflict is called a deviation point. Since the closed-loop data were collected approximately every thirty seconds, the actual deviation of the aircraft occurred somewhere between the deviation point and its previous one. Also, the corresponding ACTo's action delivered to the target aircraft should have occurred before the deviation point. This method takes a conservative approach and considers the previous point as to where the deviated aircraft took the corresponding action. This point is called a prediction point. Lastly, a conflict point is a location on the original route of an aircraft, where it is predicted to have a conflict with another aircraft.

Table 1 shows a list of the flight contextual information extracted from the collected data. Three different extraction methods were applied to obtain the listed information. The first type of contextual information is directly given by flight tracking data. Altitudes and ground speeds of aircraft at their prediction points are included in the closed-loop data. Ground speed is a summation of airspeed, actual speed generated by an aircraft, and wind speed. It does not use airspeed since it was not given by the data and the wind speed at the moment is unknown. Both variables continuous variables from zero to infinite and both aircraft in a conflict pair have their variables. The second type of information is the variables generated by computing flight tracking data. Distance and heading calculations belong to this group. Geodesic was applied to calculated distances among three different locations: the prediction to the conflict points, the conflict to the destination points, and the prediction to the destination points. They are continuous variables ranging from zero to infinite, and there are variables for each aircraft in a conflict pair. Heading angles were calculated based on the projection angle between two points. The angle can be a relative value, so bearing was applied to standardize it. There are three angular variables for each aircraft, and they are categorical. Instead of precise degrees, a degree from zero to three hundred and sixty was separated into eight pieces in a clockwise direction. Each section is forty-five degrees wide, starting from zero degrees. The operational phase of aircraft presents a stage of an aircraft from its operations. There are five main stages in a flight operation: departing, ascending, cruising, descending, and landing. Part 3 utilizes stages from ascending to descending since departing and landing stages are not responsible for the targeted ATCos for high-altitude airspace sectors. The method added intermediate stages in-between the three phases as a preparation phase to shift the stage of flight operations. These intermediates are right before and after aircraft enter or leave high-altitude sectors. Variables for the operational phases are categorical. Each aircraft has one for their prediction and conflict points because their operation phase can be different at those points, and it can affect ATCo actions. Another indicator for the operation phase is included to show whether aircraft change its phase if it is at their conflict points at the point of prediction point. The last type of flight contextual information results from computing flight tacking data with air traffic data. Unlike other variables that each aircraft has their own, there is one only categorical variable for the corresponding airspace for the conflict pairs because both aircraft are always in the same airspace at their prediction points. Airspace information is generated by comparing boundary coordinates of targeted aircraft and locational information in the closed-loop data to check whether an aircraft is inside the boundaries at its prediction point. There are three categories for the variables, which indicate three airspaces where the flight tracking data was collected. Traffic information is a special form of this type. In air traffic control systems, traffic is defined as the number of aircraft in a sector. An airspace sector is the smallest unit of airspace that an ATCo manages its traffic. Sector information can be found from the airspace map, but the coordinates are unknown. Arbitrary sectors were developed based on the information gained from the map. From the map, the area of the sectors in the targeted airspace can be measured. The size of the arbitrary sectors is set to be equivalent to the average of actual sectors' sizes. The average is a hundred square nautical mile square. The arbitrary sectors are shaped in squares, and its center is located on the prediction points. Calculation of the traffic counts aircraft that passed the arbitrary sector and checks whether their operation times is within five minutes from the timestamps of the prediction points. There is one traffic variable for both aircraft in a pair, and it is categorized into three levels: low, medium, and high, based on statistical analysis on the calculated variables for all conflict pairs.

7.2 Hierarchical structure

ATCo action has many components in it. One ATCo action can include more than one maneuver. In one maneuver, there are targeted aircraft, maneuver types, options, and other details. Part 1 applied a categorization method that separates ATCo actions with single and multiple maneuvers. Then, each maneuver was sorted into three categories, and this categorization results in a hierarchical structure for components of ATCo actions. An ATCo action is too complicated to be modeled as a single entity considering this characteristic. Part 3 developed a hierarchically structured prediction model, as shown in Figure 7.2. The structure follows the categorization method applied in Part 1. The model has three levels of sub-models. Each sub-model predicts a component of ATCo actions. The sub-model located at the top of the structure predicts the target of a maneuver. After the target is decided, its following sub-model predicts maneuver type for the predicted target. Like the ATCo action categorization method, the output of the sub-model is lateral, vertical, and speed maneuvers. Based on the predicted maneuver type, a dedicated sub-model for each type of output predicts the option of the predicted maneuver type. After the prediction from the sub-models for option predictions, predicted components from the sub-models are combined to generate an ATCo action with a single maneuver.

7.3 Input Variables

Collected data about predicted aircraft conflict pairs and their corresponding aircraft conflicts from Part 1 is applied as input to the developed prediction model. Table 2 shows the response variables for each sub-model. The variables take a particular form, which represents groups of ATCo actions in each layer of the collected ATCo actions. The models take different information from the collected ATCo actions. The sub-models for target prediction takes target from the categorized ATCo actions. A format of response variables for the sub-model of target prediction is binomial. The categorization separates targets in terms of closeness to the conflict. There are two aircraft in a pair, and one aircraft is selected by ATCo to apply an action. However, there is no systematic way to indicate the targeted aircraft. Aircraft have unique identifications, and their model numbers, manufacturer, and corresponding airliners

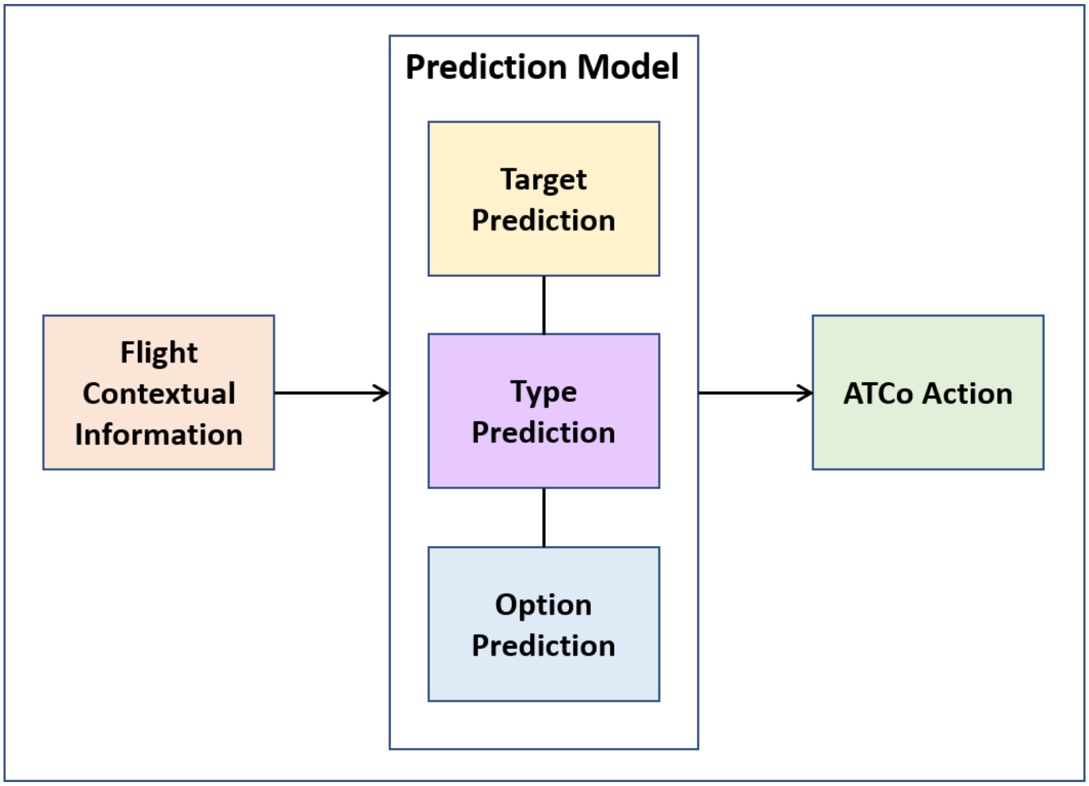


Figure 7.2.: An illustration of the hierarchical structure of the prediction model

are varied. Part 1 takes their proximities from their prediction point to their conflict points as the indicator. The targeted aircraft that are closer than their paired aircraft are grouped as one type of the target. The ones that are further away from their conflict points as another. Unlike the target prediction, the type of prediction takes multinomial responses. There are three types in the maneuvers, and each method applied to deviate the targeted aircraft considered as one type of response for the model. Like the sub-model for target prediction, the option prediction models for each response of the type prediction have binomial responses. Part 1 generalized options of maneuvers into two groups. There are many different options to apply a maneuver. It categorizes the options by whether it negatively or positively affect the variables representing each type of maneuver.

The listed twenty-five flight contextual information in Table 1 is applied as explanatory variables. The unit and type of the variables representing each information take the form that is listed in Table 1. Except for the air traffic and airspace information, each other in a pair has its own variables for the listed contextual information.

7.4 Training and Testing Dataset

Datasets created from the collected data pairs categorized ATCo actions with their corresponding flight contextual information. Two filters were applied to the collected data for preparing a dataset for the model development. There are two different types of ATCo actions: one with a single maneuver while another type with multiple maneuvers. These two types of actions cannot be applied to the same model because their dimensions are different. According to the results from Part 1, ATCo action with both single and multiple maneuvers have targeted one aircraft from the corresponding conflict pairs. However, the actions with multiple maneuvers include combinations of more than two types of maneuvers and their options. The target prediction could be conducted for both types of ATCo actions since there is one target regardless of the number of applied maneuvers for each ATCo action. However, predicting a type of maneuver and its associated one option is different from predicting multiple types and options. Unlike the single maneuvers, two additional models must be included to predict how many maneuvers to be applied and its combinations if its prediction is two maneuvers since there are three different combinations among maneuver types. As a result, a structure for the multiple maneuvers is different from that of the single maneuvers. Additionally, multiple maneuvers need further studies to understand them in detail for applications. Eventually, about twenty-five percent (about twenty-five hundred actions) of the collected ATCo actions were filtered due to having multiple maneuvers.

The filtered dataset was separated into two groups for training the prediction model and testing them. As shown in the results of Part 1, proportions of each layer in the ATCo action categorization generally do not have significant differences. However, the method applied four data selection techniques to prevent any bias that can come out from the input dataset. First, the method set the equal number of training dataset for each response in a sub-model. It calculates the number of the dataset that is seventy percent of the positive response for a binomial sub-model. If it is a multinomial model (the type prediction), the first response group is selected for the calculation. If the total number of the corresponding negative responses is greater than the calculated number, it is applied as the number of training dataset for the model. However, if the calculated number is higher than the total number of negative responses than seventy percent of the total number of negative responses is applied. For the type prediction with multinomial responses, seventy percent of the first group must be smaller than the total number of each other response group. If the condition does not satisfy, find another response' seventy percent that qualifies it. As a result, the total number of training datasets for each sub-model is the number of response types in sub-model times seventy percent of the selected response type. After selecting the portion of the training set, rest overs from the selecting portion for the training set are used as the testing set. Thus, the testing set becomes thirty percent of the selected response type and the total number of other response types subtracted by seventy percent of the selected response type for each other response types in a sub-model. After the total number of both training and testing sets is decided, the last technique randomly selects the data for each response from the dataset. There are many techniques to split data for training and testing purposes. There is no universal rule for splitting the data due to the arbitrary nature of data. Fundamentally, data may be split into three sets: training, validation, and testing. However, splitting data into two sets (training and testing) is common for measuring the prediction accuracy of the model. Moreover, the ratio of the split or application of techniques such as k-fold and "leave one out" cross-validations are highly dependent on characteristics of the dataset. This part developed twenty-four prediction models (eight sub-models with three different modeling methods). They use the same dataset, but their volumes and types of subsets for each sub-model are different. Customized data splitting techniques could generate more accurate results from each sub-model. However, the modeling methods will lose consistency in its process. Then the generalization of the results becomes an issue because results from each sub-model are case-specific. Also, results from each sub-model and modeling methods cannot be compared to each other due to having different structures. As a result, Part 3 decides to apply the most used data splitting technique (ratio of 70/30) with a matching number of response variables from each of the response types for minimizing biases.

7.5 ATCo Action Prediction Modeling

Three modeling methods were applied to develop a prediction model. The applied modeling methods are logistic regression, regression tree, and classification tree. These methods were applied due to following reasons. First, the purpose of this modeling is not developing a high-fidelity model. Instead, the essential purpose is to investigate whether the flight contextual information can be used toward ATCO action prediction. Second, the investigation require explanation between the explanatory and response variables. These modeling methods are basic methods that provide statistical explanation between the response and explanatory variables. Lastly, the applied modeling methods utilizes their unique functions to conduct models. Thus, resulted models have affected them and could show different results. Comparing results from the various methods enables whether the performance of prediction models is affected by the modeling methods or by the input variables.

Applied logistic regression used generalized linear modeling methods by McCullagh and Nelder (1989) and Chatfield et. al (2010) [45,46]. The binomial sub-models, target and type prediction sub-models, was developed with S function introduced from Hastie and Pregibon (1992) [47]. The multinomial sub-model, type prediction sub-model, was developed with fitting multinomial logistic linear modeling method by Venables and Ripley (2002) [48]. Both regression and classification trees take the method, recursive PARTitioning, based on the ideas and functions introduced by Breiman et. al (1984) for both binomial and multinomial sub-models [42]. The method builds a tree with a general two-stage procedure. The first procedure finds an explanatory variable to best split the data into two groups in terms of applied splitting functions. Then, this process is applied to each of the separated group recursively until the fine sub-group either reach a minimum size of the data or following sub-group no longer improves the performance of the model. Tree plots for each comparison were conducted to show how each explanatory variable affects the clustering. A tree pruning technique is applied to avoid overfitting. After the recursive procedure, the next procedure cross-validates the model to check any over-fitting from the branches of a tree to trim it. The technique selects a size of tree based on the original tree that minimizes the cross-validated error by computing the minimum complexity parameter.

7.6 Analysis

In general, confusion matrix was conducted to analyze performance of each model and its sub-models. The matrix show how well each model make prediction on the testing data set [49]. The table shows prediction accuracy on each response class and also can be used to calculate classification error. In addition to the confusion matrix, the prediction model and its sub-models by logistic regression modeling method was analyzed with receiver operating characteristic curve to observe relationship between rates of true positive and negative responses [50]. Lastly, concordance values are calculated, which shows ratio between concordance pairs and total possible pairs of responses to check existence of agreement in generating predected ATCo actions [51].

Two other aspects of the prediction model were investigated. First influential flight contextual information in each sub-model from each modeling methods were observed. The logistic regression modeling method calculated weight of evidence (WOE) and information value (IV) from the analysis. The WOE describes predictive power of an explanatory variable in relation to its response variable, which shows separation between different types of response variable [52]. Information value is a technique generally applied to select explanatory variables for the modeling by ranking each variable by its predictiveness of response variable. The methods applied interpretation of information value by Siddiqi (2006) used for credit scoring [53]. The tree modeling methods utilize explanatory variables that was used to branch the tree. The order of the variables in the tree from the top describes how well each variable and its parameter separates the data to explain difference between the response variables. Also, table that shows importance of variables in the prediction from calculating the sum of the goodness of split measures for each split based on Breiman et.al (1984) was applied for the investigation [42].

Another investigation is dependency between sub-models. The developed prediction model takes hierarchical structure among its sub-models that describes layers of the ATCO action categorization methods developed in Part 1. This investigation checks whether prediction from a predecessor affect the performance of the following sub-model. Prediction performance of the type and the option prediction sub-models are tested with two different datasets. First dataset is identical to the dataset given to the target prediction sub-model, which is not a subset of any other input dataset. The second dataset is a subset based on the results from the predecessor. For example, the type prediction sub-model is divided into two models that each take a subset of results from the predecessor that corresponds to one type of the response variable. If the prediction performance of the sub-models does not show significant difference, the investigation concludes a sub-model is not dependent to its predecessor

Table 7.1.: The list of the flight contextual information

Variable	Notation	Variable Type	Range	Unit	AC1&2	Context
Altitude at the predicted point	Ae	Cont.	5 - 450	FL	Y	Actual altitude
Ground speed at a prediction	Se	Cont.	130 - 644	kt	Y	Leveled ground speed
Distance from a prediction to a conflict point	Dec	Cont.	0 - 3684	km	Y	Geodesic between coordinates
Distance from a prediction to a destination	Ded	Cont.	113 - 2204		Y	
Distance from a conflict to a destination	Dcd	Cont.	78 - 1799		Y	
Heading angle from a prediction to a conflict	Bec	Cat.	1 - 8	NA	Y	Dividing bearing into 8 pieces with interval of 45 degrees from 0 degree
Heading angle from a prediction to a destination	Bed	Cat.	1 - 8		Y	
Heading angle from a conflict to a destination	Bec	Cat.	1 - 8		Y	
Operation phase at a prediction	Pe	Cat.	1 - 5		Y	5 phases from ascending to descending in sequential order
Operation phase at a conflict	Pc	Cat.	1 - 5		Y	
Operation phase change from a prediction to a conflict	Ps	Cat.	0 & 1		Y	0: False, 1: True
Air space sector traffic at a prediction	T	Cat.	1 - 3		N	Arbitrary sector
Airspace	S	Cat.	1 - 3		N	1: ZLA, 2: ZOB, and 3: ZTL

8. PART 3: RESULTS

Figure 8.1 shows the resulted structure of the prediction model. The results show that the type prediction sub-model is not dependent to the target prediction model, but the option prediction sub-models are dependent to the type prediction sub-model. The overall performance of all three models is low due to poor prediction performance in type and lateral option predictions. The prediction model by the regression tree modeling method results in the worst performance due to inferior performance on its type prediction. Besides, there are some differences between the logistic regression model and tree models. The accuracy of the target sub-model by logistic regression is better than other methods. The differences are smaller than ten percent. However, consistency in predicting its types of responses have significant differences. The logistic regression model shows consistent prediction accuracy, while others show forty percent differences between the response types. The differences among the modeling methods are clearly represented from the type predictions. One factor that is expected to cause them is being multinomial models. However, prediction accuracies of speed maneuvers are consistent across the methods. Additionally, both the logistic regression and the regression tree are greatly suffered by the prediction of the vertical maneuvers. Only the speed maneuver prediction show consistency across the models. The performance of option prediction sub-models by the tree modeling methods show identical results. In general, their performance is lower than those of the logistic regression. However, the prediction accuracy of vertical option prediction sub-models shows exceptional performance, which needs attention on relationships among the responses and influential explanatory variables.

Table 8.1 shows the misclassification errors of the type prediction by training with the subset created by responses from the target predictions. From the comparison

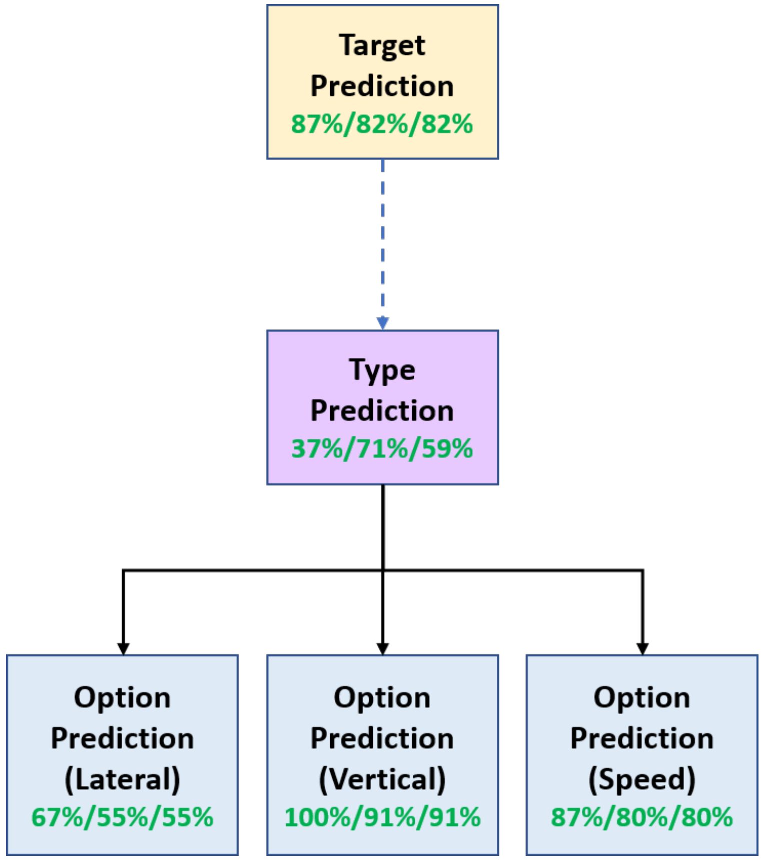


Figure 8.1.: An overview of Part 3: Results

between their counterparts presented above, the performance of the prediction sub-models with the subset is slightly worse than the one without it. It implies that the type prediction may not be dependent on its upper layer of the ATCo action categorization. However, it is difficult to conclude since their prediction accuracies are too low. It is not clear whether the relationship between response and explanatory variables are clearly explained in the sub-models.

Table 8.2 shows the misclassification errors of the option prediction sub-models without subsets created by responses from the type predictions. The average misclassification errors of sub-models of three options from the above (the logistic regression: 15.56%, the classification, and regression trees: 24.59%) are better than the perfor-

Table 8.1.: Prediction performance of type prediction sub-models for the dependency test

	No Subset	Subset (Positive)	Subset (Negative)
Logistic Regression	63%	71%	58%
Regression Tree	71%	91%	61%
Classification Tree	41%	69%	69%

mance shown in Table 2. The results can be concluded as the option predictions are dependent on the type predictions.

Table 8.2.: Prediction performance of option prediction sub-models for the dependency test

	No subset	Subset (Lateral)	Subset (Vertical)	Subset (Speed)
Logistic Regression	28%	67%	55%	55%
Regression Tree	28%	100%	91%	91%
Classification Tree	26%	87%	80%	80%

Table 8.3 shows the information values of each sub-model. Values greater than zero were listed in the table. Values above 0.3 are interpreted as the corresponding variables are strong predictors. The target prediction has five strong predictors while the type prediction has three, the lateral option prediction has two, the vertical option prediction has six, the speed option prediction has two. The speed of untargeted aircraft at their prediction points for the target prediction model has the highest value. However, the type prediction has the greatest number of strong predictors, and it does not have any weak predictors. The speed option prediction only has weak predictors. Lastly, lateral option prediction does not have a predictor with a value above one, and it has the shortest list. The speed at the prediction point from

the target, type, and vertical option predictions is selected as the most influential predictor. However, the target prediction selects those of untargeted aircraft while other sub-models choose from the targeted aircraft. Also, either the speed or the altitude at the prediction points is selected as the most influential predictor. At the same time, another one follows the next except for the lateral option prediction. The lateral option prediction is the only sub-model that has predictors about distance variables. Generally, the distance variables follow the speed and altitude variables. However, the speed option prediction only deals with the altitude and speed variables of both aircraft.

Table 8.3.: Information values of the flight contextual information from prediction modeling

Target		Type		Option (Lateral)		Option (Vertical)		Option (Speed)	
VARS	IV	VARS	IV	VARS	IV	VARS	IV	VARS	IV
se2	3.0473	se1	2.8558	dec1	0.8133	se1	2.8558	ae1	2.5932
ae2	2.3746	ae1	2.5302	dcd2	0.4199	ae1	2.5302	se1	1.5442
ded1	0.3789	dec2	2.0006	dec2	0.2337	dec2	2.0006	ae2	0.154
ded2	0.3167	ded1	1.5184			ded1	1.5184	se2	0.1113
dec1	0.3145	dec1	1.2266			dec1	1.2266		
se1	0.2531	dcd2	0.5558			dcd2	0.5558		

Table 8.4 and 8.5 shows the essential variables selected by the regression and classification tree modeling methods. The variables with values of less than five percent are filtered. The listed variables of both methods for the target prediction is almost identical. The results show that the speed of untargeted aircraft at their prediction points is the most influential variable from both modeling methods. The altitude of untargeted aircraft follows next. Besides the distance variables showed at the information variables, variables about operational phases and heading angle appears in the list. The operational phase of untargeted aircraft at the prediction points takes twelve percent, which is the third place, and the heading angle of that targeted aircraft at the prediction points follows with eleven percent. The resulted trees from both modeling methods also selected the speed of untargeted aircraft at

the prediction points as the first node. The type prediction models show differences in their lists. The regression tree has four variables with proportions higher than ten percent, while the classification tree model has two. The proportions of variables are slightly different.

Table 8.4.: Influential variables of the flight contextual information from target and type prediction modeling

Target				Type			
Regression Tree		Classification Tree		Regression Tree		Classification Tree	
VARS	Reg Tree	VARS	Class Tree	VARS	Class Tree	VARS	Class Tree
se2	16%	se2	16%	dec1	15%	dec2	13%
ae2	15%	ae2	15%	dec2	13%	dec1	13%
pe2	12%	pe2	12%	ded1	10%	se1	9%
bec1	11%	bec1	11%	ae1	10%	ae1	9%
dec2	9%	dec2	10%	se1	7%	ae2	8%
dec1	7%	dec1	7%	dcd1	7%	se2	6%
pc2	7%	pc2	7%	se2	6%	bec1	6%
ps2	6%	ps2	6%				
bed1	5%						

Moreover, the regression tree sub-model has two variables that are not in the list of the classification tree sub-model. The distance from the conflict point to the destination and from prediction point to the destination of targeted aircraft appeared in the list as third and sixth places. At the same time, the classification tree sub-model has a heading angle of targeted aircraft in the last place. Unlike their most important variables, both modeling methods choose the speed of targeted aircraft at the prediction points as the first node to branch. The lateral option prediction sub-models of both methods have an identical list for the first five variables. Both proportions and types of variables are different after then. However, both methods choose the distance between prediction and conflict points of targeted aircraft as the first node in their trees. The variables list for the vertical option predictions of the two methods shows identical results. The listed variables all the full list and the least essential variables take at least twice more proportions than those from other sub-

Table 8.5.: Influential variables of the flight contextual information from option prediction modeling

Option (Lateral)				Option (Vertical)				Option (Speed)			
Regression Tree		Classification Tree		Regression Tree		Classification Tree		Regression Tree		Classification Tree	
VARS	Importance	VARS	Importance	VARS	Importance	VARS	Importance	VARS	Importance	VARS	Importance
dec1	19%	dec1	22%	ae1	21%	ae1	21%	ae1	21%	ae1	22%
dec2	17%	dec2	16%	pe1	20%	pe1	20%	pe1	20%	pe1	22%
ded1	10%	ded1	11%	ps1	19%	ps1	20%	ps1	13%	ps1	14%
dcd1	8%	dcd1	8%	dec1	14%	dec1	13%	se1	11%	se1	12%
ded2	7%	ded2	8%	se1	13%	se1	13%	dec1	7%	dec1	7%
se2	6%	bec1	6%	dec2	12%	dec2	12%	dec2	5%	dec2	5%
bec1	5%	dcd2	6%								
dcd2	5%	bcd1	5%								
se1	5%	bed1	5%								

models. Their trees select the altitude of targeted aircraft at the prediction points as the first node. The results from the speed option prediction sub-models show an identical list for both methods. Their top three variables are identical to those of the vertical option predictions. Also, their trees select the altitude of targeted aircraft at the prediction points as the first node.

8.1 Logistic Regression Model

The overall performance of the prediction model developed with logistic regression modeling methods is twenty-seven percent. The performance accuracy is low due to sub-models related to predicting lateral maneuvers. Table 8.6 shows the confusion matrix of the target prediction sub-model. The misclassification error of the sub-model is about thirteen percent. In other words, its prediction accuracy is about eighty-eight percent. The prediction on target aircraft that is further away from their conflict points is about eighty-eight percent, and that of closer aircraft is about eighty-six percent. Their performances are similar. However, the closer aircraft has a much larger number of testing datasets compare to their counterparts. Figure 8.2 shows the receiver operating characteristics (ROC) curve of the target prediction sub-model. The area under the roc curve (about eighty percent) and its shape of the curve support the high performance of the sub-model. The concordance value being about eighty-eight percent also supports other evidence since the concordance value of the perfect model is a hundred percent.

Table 8.6.: Confusion matrix of the target prediction sub-model by logistic regression

Responses		Actual	
		Further	Closer
Predicted	Further	22	3
	Closer	23	146

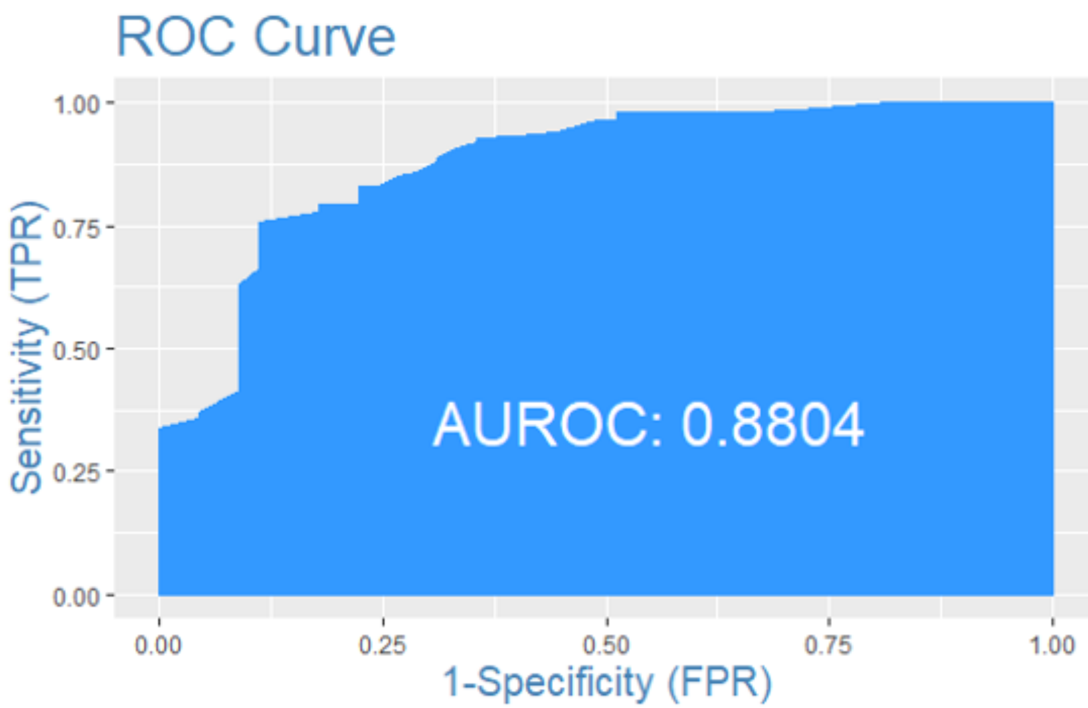


Figure 8.2.: A receiver operating characteristics curve of the target prediction sub-model

Table 8.7 shows the confusion matrix of the type prediction sub-model. Its misclassification error is about sixty-two percent. The prediction accuracy of the lateral maneuver is forty-two percent. In comparison, those of the vertical and speed maneuvers are twenty-six and fifty-three percent each. Their performances are low. The probability of randomly selecting from three categorical responses is thirty-three percent. Accuracies for lateral and speed maneuvers are higher than the random probability. However, the performance of a vertical maneuver is about twice lower than others. Also, the overall performance of the type prediction sub-model can be lower than others since it is a multinomial model while others are binomial. However, its overall performance being thirty-seven percent is no better than random selection.

Table 8.8 shows the confusion matrix of the option prediction sub-model for lateral options. Its misclassification error is about thirty-three percent. As the performance of the type prediction sub-model, option prediction for the lateral maneuvers is also

Table 8.7.: Confusion matrix of the type prediction sub-model by logistic regression

Reponses		Actual		
		Lateral	Vertical	Speed
Predicted	Lateral	14	8	11
	Vertical	13	21	46
	Speed	8	13	24

low. The prediction performance of negative options is a hundred percent, but the tested number of data is small. The performance accuracy of positive option is sixty-seven percent. Figure 8.3 shows a ROC graph of the model. The area under the curve is about sixty-four percent of the area, and the shape of the curve is almost linear. This evidence concludes that the performance of this model is low.

Table 8.8.: Confusion matrix of the lateral option prediction sub-model by logistic regression

Responses		Actual	
		Negative	Positive
Predicted	Negative	2	0
	Positive	10	19

Table 8.9 shows the confusion matrix of the option prediction sub-model for vertical maneuvers. Its misclassification error is zero percent. It tells flight contextual information is perfectly explaining and predicting the data. ROC curve in Figure 8.4 also supports the results by filling the area with its curve. Lastly, the concordance value is also a hundred percent. All results show that the performance of the sub-model is too high. Two investigation methods were conducted to understand the perfect accuracy. First, when the fitted probability is one, there is a high possibility that one or more predictor is segregating the responses perfectly. The IV values of the

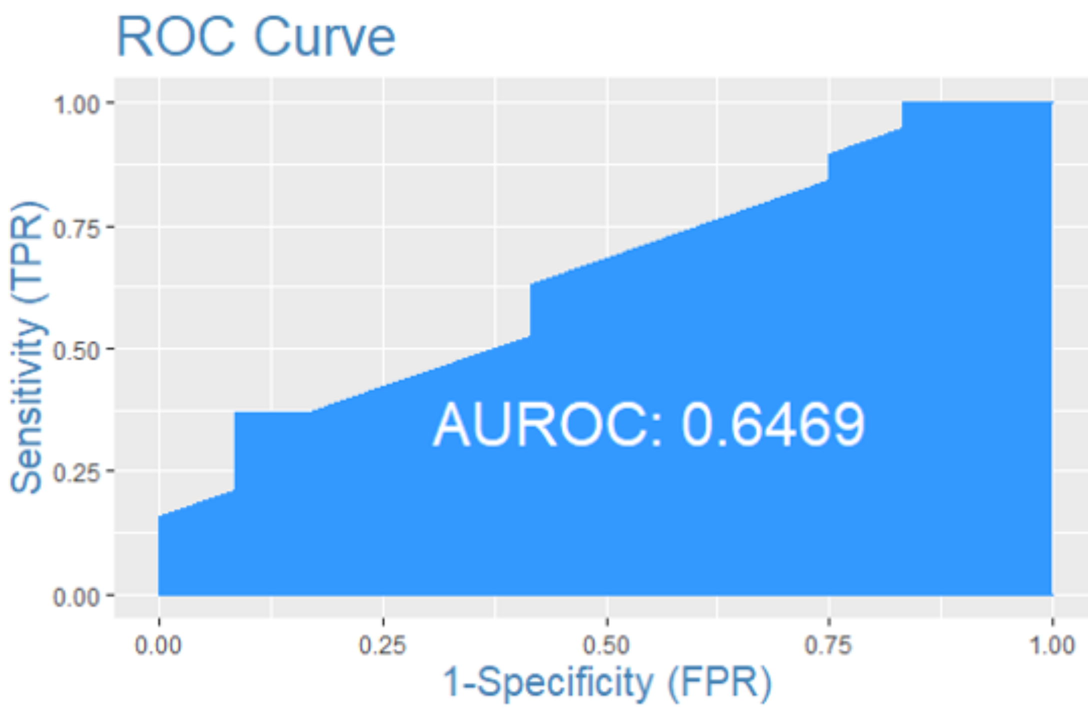


Figure 8.3.: A receiver operating characteristics curve of the lateral option prediction sub-model

model do not show any difference compare to those of other models, as shown in Table 8.3. Next, a stepwise logistic regression was conducted to identify any predictors that perfectly separates the response variables. The results of the regression analysis showed that stepwise logistic regression selected four variables (speed and altitude of target aircraft, distances to the conflicts points on both aircraft) are affecting the model the most. However, Table 8.10 shows that the P-value of the null model is low while that of residual is one. It implies that the model does not make a good prediction with the predictors but with its intercept. The value of the intercept is about three thousand, and the coefficients of predictors are low except for the altitude of the target (about -8). It tells us that the model is highly dependent on the value of the altitude of the target. If the altitude is low, the model predicts option as a positive, which results in climbing up and vice versa.

Table 8.9.: Confusion matrix of the vertical option prediction sub-model by logistic regression

Responses		Actual	
		Negative	Positive
Predicted	Negative	27	0
	Positive	0	17

Table 8.10.: An analysis from the stepwise logistic regression on the vertical option prediction

NULL			Residual		
Degree of Freedom	Deviance	P-value	Degree of Freedom	Deviance	P-value
77	108.1	0.011	73	0.0000000005228	1

Table 8.11 shows the confusion matric of the option prediction sub-model for speed maneuvers. Its misclassification error is about thirteen percent. Prediction accuracy of the negative responses is eighty-six percent, and its positive response is eighty-seven percent. Figure 8.5 shows a ROC curve of the prediction sub-model. The area under the ROC curve is about eighty-nine percent, and the shape of the curve is stable concave up. Lastly, its concordance value is about eighty-nine percent. This evidence shows that the prediction performance of the sub-model is high and reliable.

Table 8.11.: Confusion matrix of the speed option prediction sub-model by logistic regression

Responses		Actual	
		Negative	Positive
Predicted	Negative	87	14
	Positive	8	55

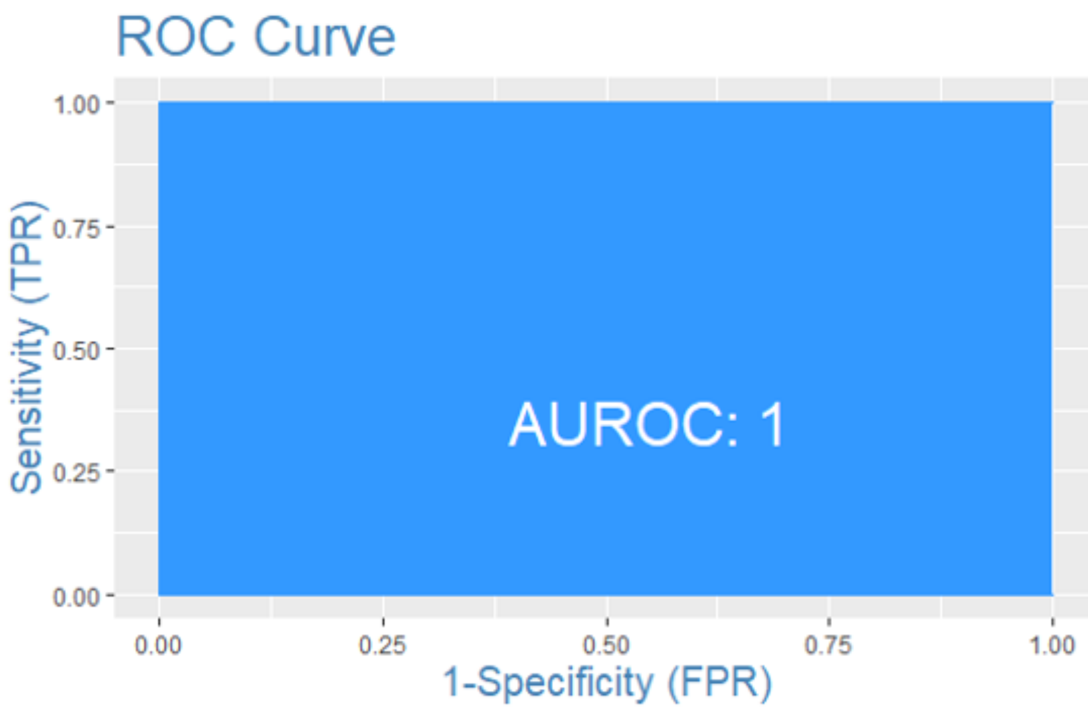


Figure 8.4.: A receiver operating characteristics curve of the vertical option prediction sub-model

8.2 Regression Tree Model

The overall performance of the prediction model developed with regression tree modeling methods is eighteen percent. Like the prediction model by logistic regression modeling, the performance accuracy is low due to sub-models related to predicting lateral maneuvers. Table 8.12 shows the confusion matrix of the target prediction sub-model. Its misclassification error is about eighteen percent. Prediction accuracy of negative responses is fifty-seven percent, and its positive response is ninety-six percent. The accuracy of the negative responses is close to the probability of random selection for binomial responses. Figure 8.6 shows the cross-validation graph of the sub-model. The relative error values continuously decrease before the last branch of the tree and slightly increase at the end. It implies that there is evidence of weak overfitting.

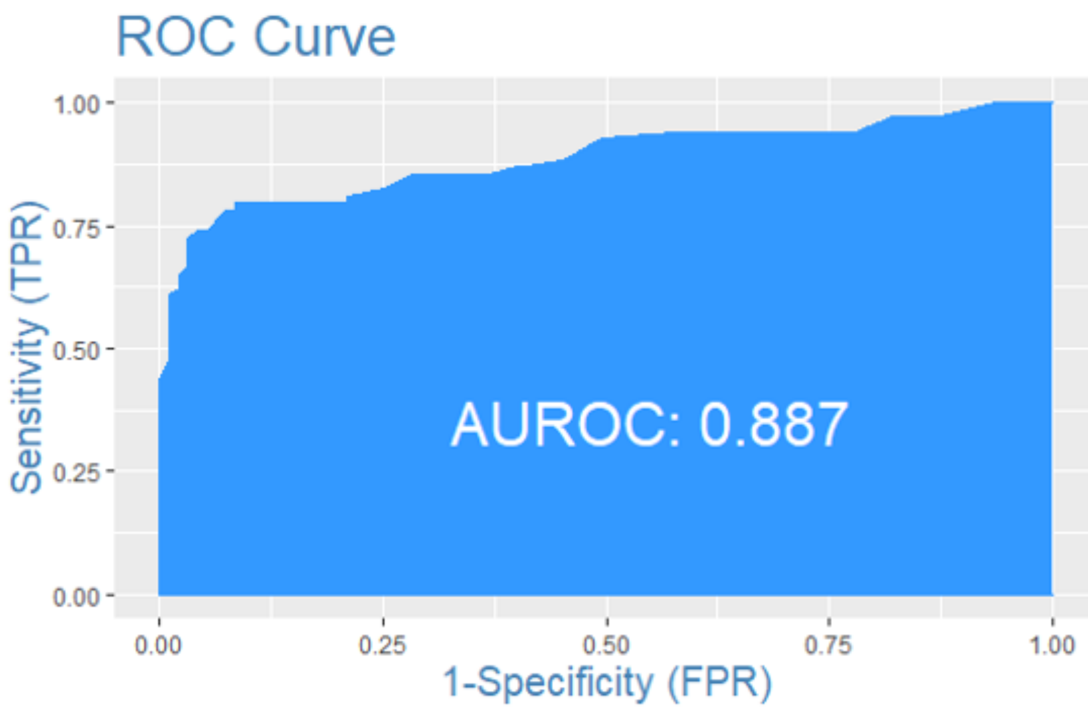


Figure 8.5.: A receiver operating characteristics curve of the speed option prediction sub-Model

Table 8.12.: Confusion matrix of the target prediction sub-model by regression tree

Responses		Actual	
		Further	Closer
Predicted	Further	40	30
	Closer	5	119

Table 8.13 shows the confusion matrix of the type prediction sub-model. Its misclassification error is about seventy-one percent. Except for the speed maneuver prediction, the other two types show significantly low accuracies compare to the probability of random selection from three options. Figure 8.7 shows the cross-validation graph of the sub-model. The changes in the relative errors increase from the first

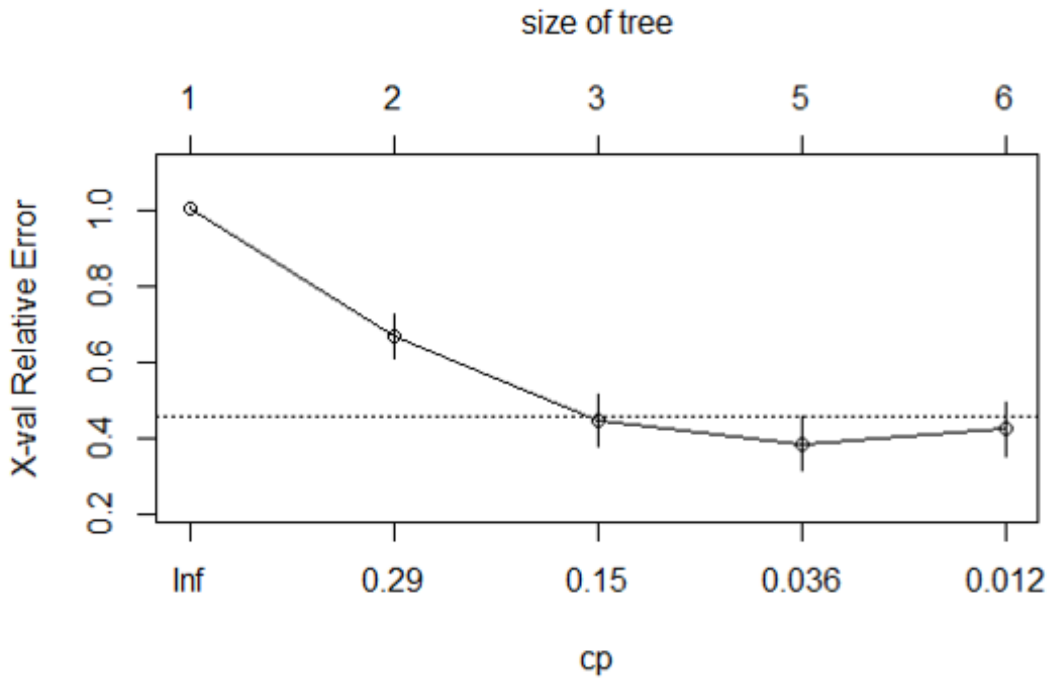


Figure 8.6.: A cross-validation graph of the target prediction sub-model by regression tree

branch of the tree. It implies that the performance of the model is insufficient to make predictions.

Table 8.13.: Confusion matrix of the type prediction sub-model by regression tree

Reponses		Actual		
		Lateral	Vertical	Speed
Predicted	Lateral	10	18	17
	Vertical	16	12	40
	Speed	9	12	24

Table 8.14 shows the confusion matrix of the option prediction sub-model for lateral options. Its misclassification error is about forty-five percent. As the perfor-

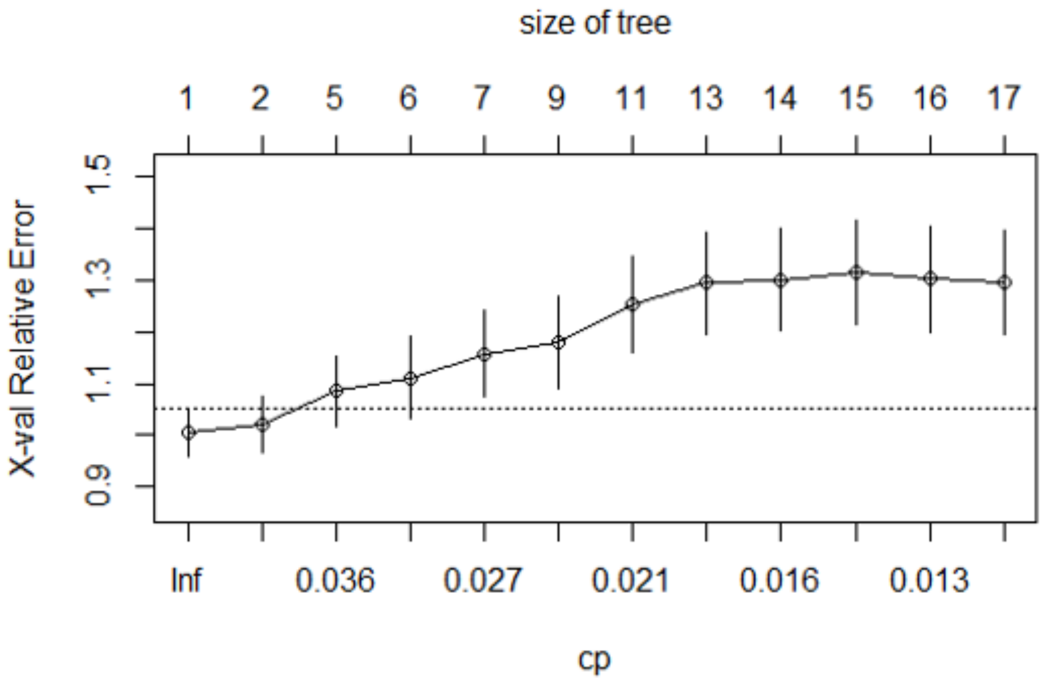


Figure 8.7.: A cross-validation graph of the type prediction sub-model by regression tree

mance of the type prediction sub-model, option prediction for the lateral maneuvers also shows low performance. However, it shows worse prediction accuracy compare to the sub-model by the logistic regression modeling method. The Prediction accuracy of the negative response is forty-five percent, while its counterpart is seventy-eight percent. Figure 8.8 shows the cross-validation graph of the sub-model. Its relative error values only decrease after the first node then goes above the value of the first nodes.

Table 8.15 shows the confusion matrix of the option prediction sub-model for vertical options. Its misclassification error is about fourteen percent. Prediction accuracy of the negative options is ninety percent, while its positive option is ninety-three percent. Figure 8.9 shows the cross-validation graph. Relative error drops significantly at the second branching. It decreases after the first node then slightly increases afterward, which implies evidence of overfitting.

Table 8.14.: Confusion matrix of the lateral option prediction sub-model by regression tree

Responses		Actual	
		Negative	Positive
Predicted	Negative	10	12
	Positive	2	7

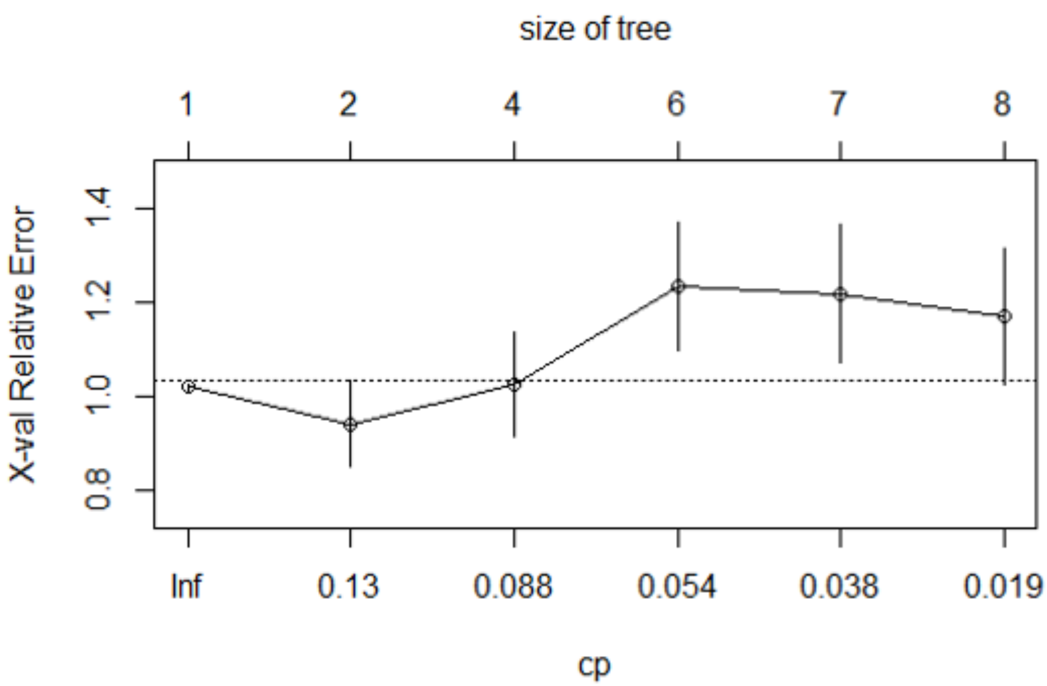


Figure 8.8.: A cross-validation graph of the lateral option prediction sub-model by regression tree

Table 8.16 shows the confusion matrix of the option prediction sub-model for speed options. Its misclassification error is about twenty percent. Prediction accuracy of the negative options is eighty-five percent, and its positive option is seventy-five percent. Figure 8.10 shows the cross-validation group of the sub-model. The relative error

Table 8.15.: Confusion matrix of the vertical option prediction sub-model by regression tree

Responses		Actual	
		Negative	Positive
Predicted	Negative	26	3
	Positive	1	14

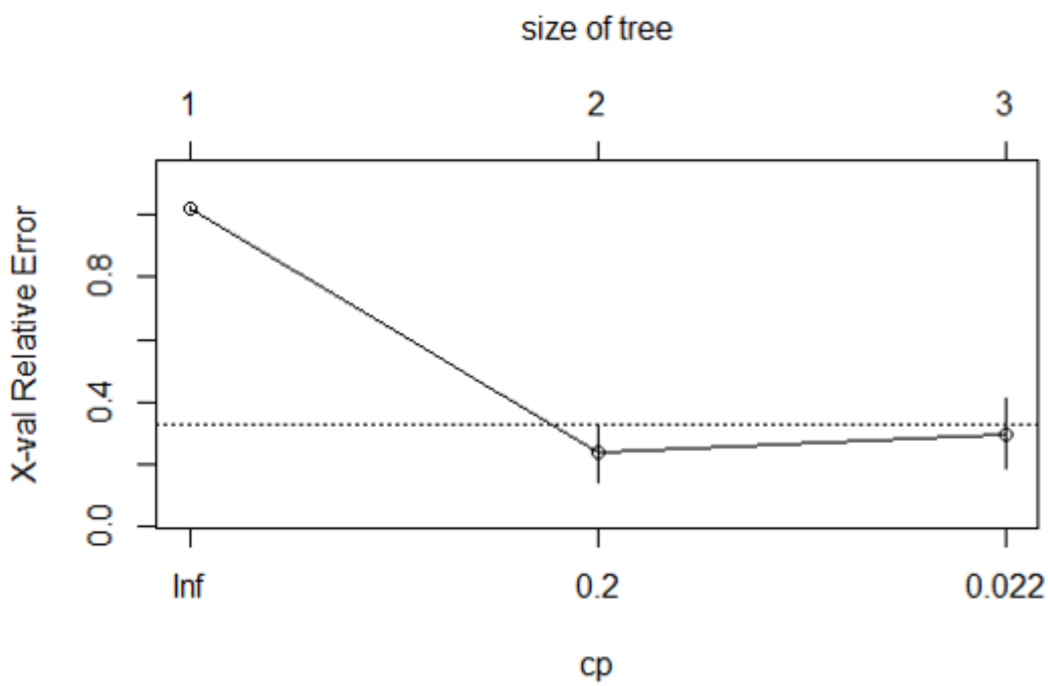


Figure 8.9.: A cross-validation graph of the vertical option prediction sub-model by regression tree

significantly reduces after the first branching and continuous to decrease until the fourth, then the parameter increases back and flattens.

Table 8.16.: Confusion matrix of the speed option prediction sub-model by regression tree

Responses		Actual	
		Negative	Positive
Predicted	Negative	77	14
	Positive	18	55

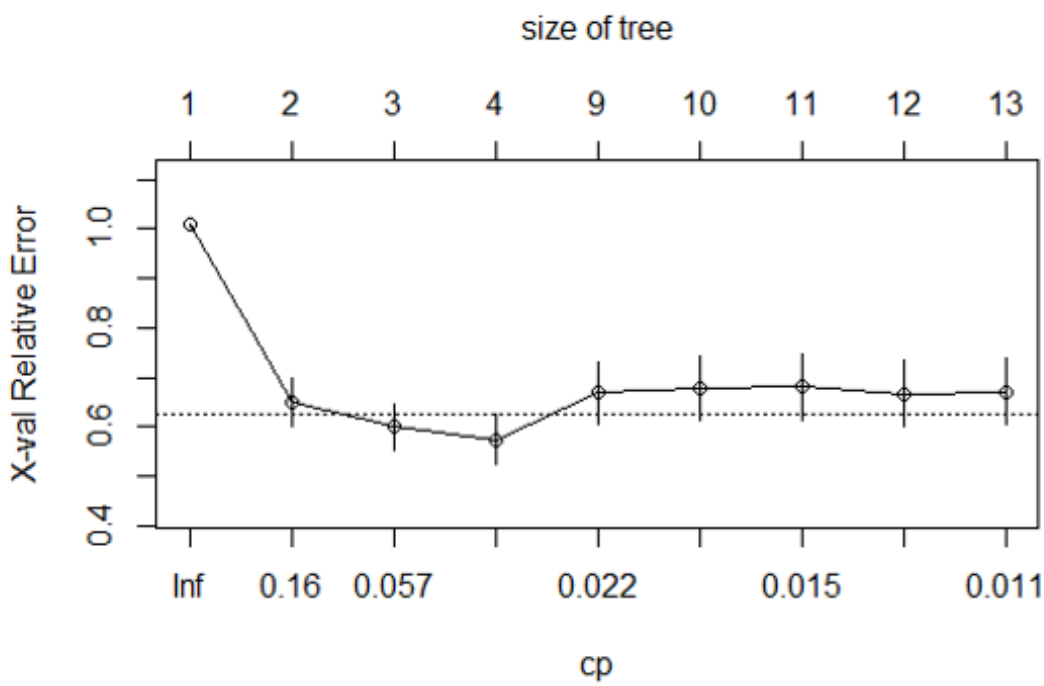


Figure 8.10.: A cross-validation graph of the speed option prediction sub-model by regression tree

8.3 Classification Tree Model

The overall performance of the prediction model developed with classification tree modeling methods is about twenty-five percent. The results are like the prediction model by the regression tree except for the type prediction and the results from cross-validation. Like other prediction models, the performance accuracy is low due to sub-models related to predicting lateral maneuvers. Table 8.17 shows the confusion matrix of the target prediction sub-model. Its misclassification error is about eighteen percent. The prediction accuracy between its responses is significant. However, the closer aircraft has a much larger number of testing datasets compare to their counterparts. Prediction accuracy of negative responses is fifty-seven percent, and its positive response is ninety-six percent. Figure 8.11 shows the cross-validation graph of the sub-model. The relative error values continuously reduce, which means there is no evidence of overfitting.

Table 8.17.: Confusion matrix of the target prediction sub-model by classification tree

Responses		Actual	
		Further	Closer
Predicted	Further	40	30
	Closer	5	119

Table 8.18 shows the confusion matrix of the type prediction sub-model. Its misclassification error is about fifty-nine percent. The sub-model shows similar results as the sub-model by the logistic regression modeling method. Again, its low performance is due to the lateral type prediction. The prediction accuracy of the lateral maneuvers is thirty-one percent. The prediction accuracy of the vertical maneuvers is thirty-two percent. Lastly, the prediction accuracy of the speed maneuvers is fifty-five percent. Accuracies of lateral and vertical maneuvers are lower than the probability of random selection. Figure 8.12 shows the cross-validation graph of the sub-model. The curve fluctuates as the branching of the tree continues.s

Table 8.19 shows the confusion matrix of the option prediction sub-model for lateral options. Its misclassification error is about forty-five percent. As the performance of the type prediction sub-model, option prediction for the lateral maneuvers

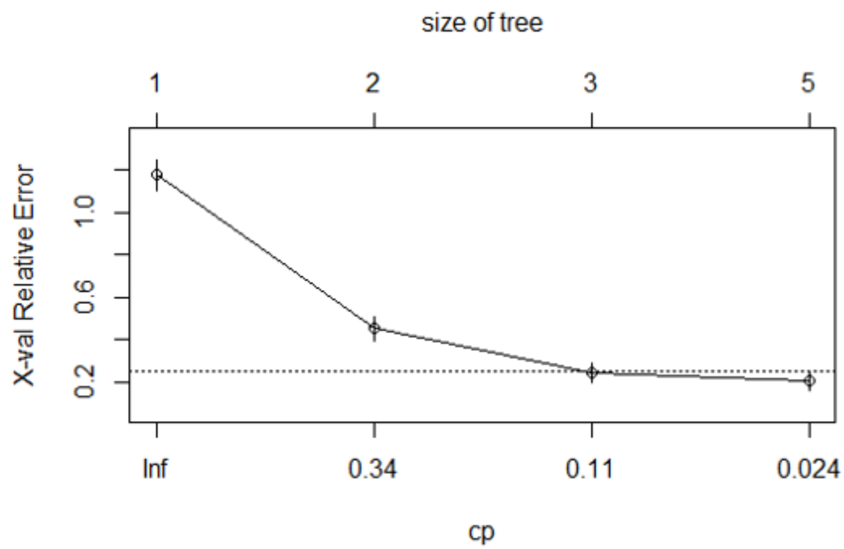


Figure 8.11.: A cross-validation graph of the target prediction sub-model by classification tree

Table 8.18.: Confusion matrix of the type prediction sub-model by classification tree

Reponses		Actual		
		Lateral	Vertical	Speed
Predicted	Lateral	13	10	19
	Vertical	8	16	26
	Speed	14	16	36

also shows low performance. However, it shows worse prediction accuracy compare to the sub-model by the logistic regression modeling method. The Prediction accuracy of the negative response is forty-five percent, while its counterpart is seventy-eight percent. Figure 8.13 shows the cross-validation graph of the sub-model. Its relative error values only decrease after the first node than continuously goes up slightly.

Table 8.20 shows the confusion matrix of the option prediction sub-model for vertical options. Its misclassification error is about fourteen percent. Prediction

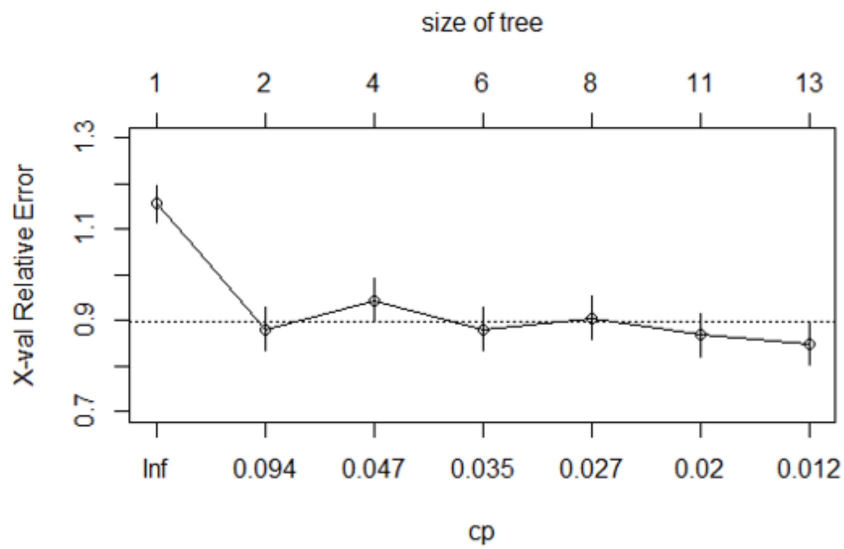


Figure 8.12.: A cross-validation graph of the type prediction sub-model by classification tree

Table 8.19.: Confusion matrix of the lateral option prediction sub-model by classification tree

<table>
<tr><td colspan="2" rowspan="2">Responses</td><td colspan="2">Actual</td></tr>
<tr><td>Negative</td><td>Positive</td></tr>
<tr><td rowspan="2">Predicted</td><td>Negative</td><td>10</td><td>12</td></tr>
<tr><td>Positive</td><td>2</td><td>7</td></tr>
</table>

accuracy of the negative options is ninety percent, while its positive option is ninety-three percent. Figure 8.14 shows the cross-validation graph. Relative error drops significantly at the second branching. The values decrease over time, but the size of the tree is significantly smaller than other trees.

Table 8.21 shows the confusion matrix of the option prediction sub-model for speed options. Its misclassification error is about twenty percent. Prediction accuracy of the negative options is eighty-five percent, and its positive option is seventy-five

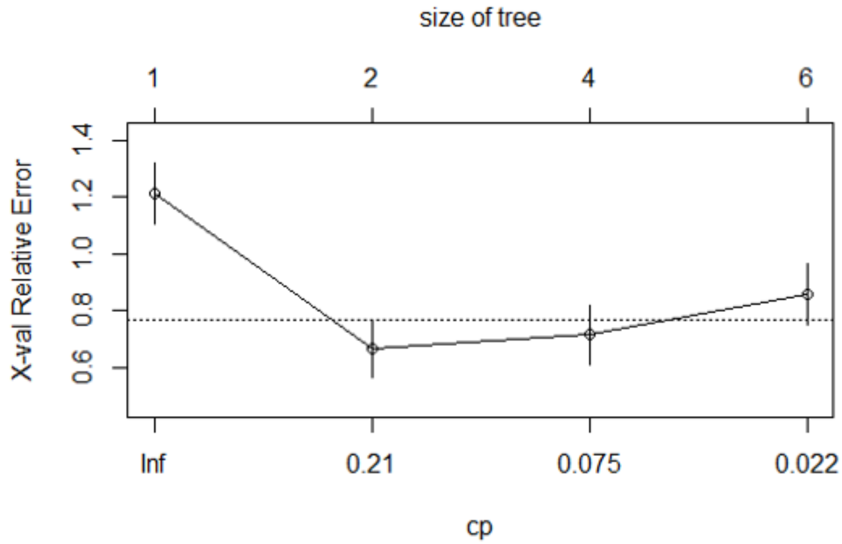


Figure 8.13.: A cross-validation graph of the lateral option prediction sub-model by classification tree

Table 8.20.: Confusion matrix of the vertical option prediction sub-model by classification tree

Responses		Actual	
		Negative	Positive
Predicted	Negative	26	3
	Positive	1	14

percent. Figure 8.15 shows the cross-validation group of the sub-model. The relative error significantly reduces after the first branching and increases back slightly, then flattened.

Table 8.21.: Confusion matrix of the speed option prediction sub-model by classification tree

Responses		Actual	
		Negative	Positive
Predicted	Negative	77	14
	Positive	18	55

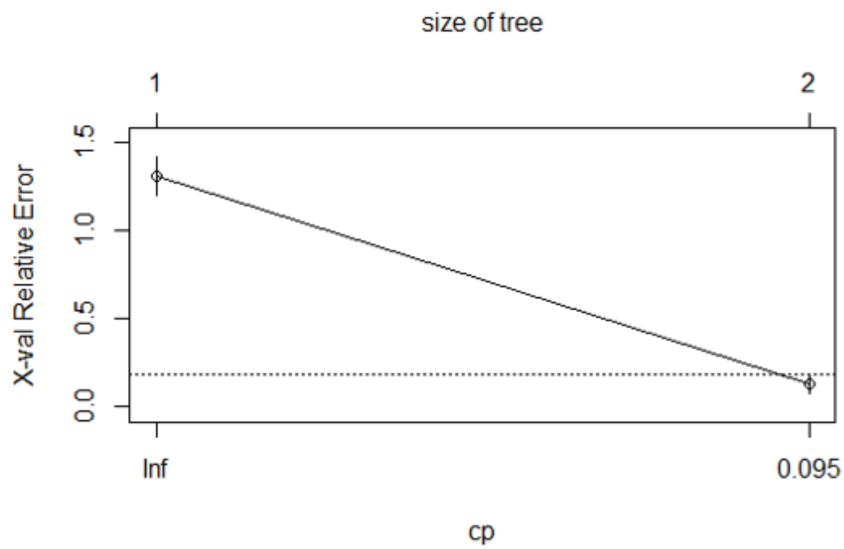


Figure 8.14.: A cross-validation graph of the vertical option prediction sub-model by classification tree

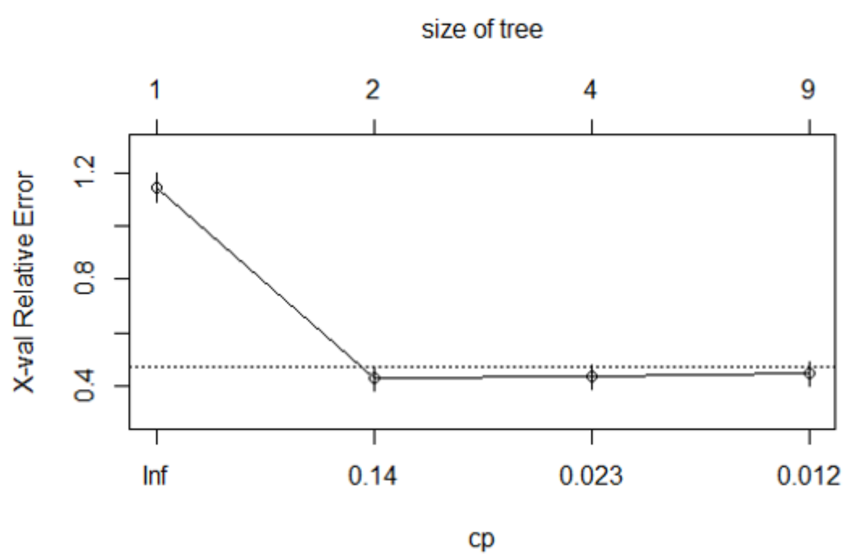


Figure 8.15.: A cross-validation graph of the speed option prediction sub-model by classification tree

9. CONCLUSIONS AND DISCUSSIONS

The goal of this work is to design a method to evaluate existing ATCo action prediction models and developing an ATCo action prediction model. The evaluation was conducted by comparing the performance of solutions from an existing prediction model against actual ATCo actions on associated predicted aircraft conflicts. The model development was conducted based on utilizing contextual flight information. The collection of ATCo actions from flight data enables these two parts of the goal. The collected data was applied to a series of algorithms that identified ATCo actions and their corresponding predicted aircraft conflicts from open and closed-loop data of flight tracking data. The data collection phase of this study took a different path from conventional studies to overcome their limitations. It showed that a large scale of ATCo actions could be collected from data-driven approaches. The data-driven approach can technically and practically collect all ATCo actions. Also, the collected data is actual ATCo actions that are not from experiments or simulations like conventional studies. Lastly, the data collected in this way enables validation of the conventional studies that did not have methods to check the validity of their models in the real-world. So far, we do not know how ATCos are managing aircraft conflicts. One of the purposes of studying ATCo is to use the knowledge to improve air traffic control systems. Results and methods from this work suggest how data-driven approaches contribute to our knowledge about ATCos.

Part1 introduced a method to identify predicted conflict pairs and corresponding deviations and found the information from public flight tracking data. The algorithms and the data used for this study presented that resulted in aircraft trajectory data can be utilized to predict and to trace back an invisible intention behind the scene. Also, the method showed a case that ATCo actions could be collected with public information. Lastly, the structure of the method outputs can be used to conduct a more sophisticated analysis. Besides investigating characteristics coming from each airspace, those three airspaces were selected to measure the generalization of the results from the collected data. Collecting data from all airspaces is technically plausible, but it is not practical. Thus, the airspaces were selected for the following reasons. They are far away from each other. If airspaces were adjacent or close to each other, there is a higher chance of having overlapping aircraft. Also, these airspaces are geologically located on the different sides of the U.S continent. It makes them include major airports on the corresponding portion of the states, which results in different types of air traffic. For example, most of the traffic in ZOB is going from the west to east and vice versa, while that of ZTL is north to south. The results from Figure 4.1 also supports the generalization issue. About the same number of flights were collected from each airspace. The total number between ZOB and ZTL is almost the same, and ZLA has approximately 20% more flights than others. The only two factors that share among the airspaces are that they are the busiest airspaces, and the data was collected in an identical time period. Moreover, the filtration process excluded a similar number of aircraft. Similarities in these airspaces also can be found from the categorized ATCo actions. The daily analysis of the total number of collected flights shows that there are some daily differences, but there is no difference among the airspaces. The amount of aircraft traffic and types can be affected by time factors. However, airline companies operate flights between airports on a routine or daily basis. It can be identified by flight numbers assigned to aircraft. Each aircraft has its unique flight ID, but its flight number can be identical if its airline, departure, and arrival are identical. The collected data could not verify it because it does not include the flight number to find those aircraft. The analysis by individual airspace show some differences, but the categorization does not show any significant differences among the groups in each layer. These findings suggest that there are no unique characteristics among the airspaces. Also, relatively equally distributed proportions of the ATCo actions suggest that there is no maneuver that ATCos favored to apply to resolve the conflicts. The results found that a large portion of the ATCo actions includes multiple maneuvers. Further studies on this type of ATCo action are required to understand them. Lastly, the results showed that ATCos applied their actions on only one aircraft in an aircraft conflict pair. There are shortcomings to Part 1. Since it is a data-driven approach, the quality of the results is highly dependent on credibility and the accuracy of the data. The proposed method had to make strong assumptions due to the absence of specific information in the open-loop data. The closed-loop data only shows locational and status of aircraft approximately every thirty seconds. This information may be enough to simulate aircraft activities, but missing information in between recorded points can be significant. Also, having ground speed instead of airspeed made the method to apply a leveling, which has impacts on the results related to the speed deviations. External factors that were not considered in this study, such as weather information, could be reasons for some of the identified deviations. Some conflicts were subject to be considered as false-positive actions that a pair of aircraft were not precisely conflicting. However, ATCo decided to intervene regardless of it. Lastly, there are complicated types of aircraft conflicts that involve more than two aircraft. Some aircraft conflicts detected by the algorithms could be parts of those complicated conflicts. The algorithms could be improved to catch such situations.

Part 2 evaluated an existing prediction model against actual ATCo actions. I developed three comparisons methods to evaluate the model, both qualitative and quantitatively. A series of conditions were considered to select a model from reviewed models. A technique to systematically disassemble the selected model into three parts and transformed them into a form that can take the collected data as input and generate categorical and executable solutions. The results found that only ten percent of the predicted aircraft conflicts had ATCo actions that are categorically identical to the model solutions. Even considering those that are similar, and the conflicts with categorically different ATCo actions that can take the model solution, the performance of the model is not high. The feature and quantitative comparisons showed that a large portion of the conflicts has categorically different ATCo actions from the model solutions because of operational limitations. The model solution often results in targeting an aircraft in a critical phase that is not less safe than targeting another aircraft. Also, a small portion of predicted conflicts causes another conflict with nearby aircraft if they have taken the model solutions. It implies that the solutions generated by the selected model do not consider the traffic in the area. The feature comparison may need further analysis because it could not clearly explain the roles of some flight contextual information in terms of flight operations and air traffic controls. Also, it could not identify a clear difference between some groups. This result suggests that applied flight contextual information may not include some information that could explain differences. Part 2 evaluated one model, and it is possible that there are other models that may perform better than the selected one. The results should not be generalized, but it should be noted that the selected model is a result of multiple studies. Thus, evaluating other prediction models could provide more in-depth knowledge regarding the performance of the existing models. As future work, evaluating another type of prediction models, mathematical models, can be evaluated with the developed methods. Also, other comparison methods could be considered, such as economic analysis between the model solutions and applied ATCo actions.

Part 3 developed an ATCo action prediction model. Unlike the conventional model evaluated from Part2, the developed model is based on the data collected from Part 1. The flight contextual information was generated from the collected data that represents the physical and operational status of aircraft conflict pairs. The developed model took a hierarchical structure consist of multiple sub-models for predicting each layer of the ATCo actions. The resulted performance of the prediction model has a wide range due to a significant gap between the two groups of sub-models. The sub-models about lateral maneuvers have significantly low performance than others. The type prediction model which has multinomial responses could have lower performance due to extra response type compare to other sub-models. However, its results show that the prediction on the vertical and speed maneuvers in the type prediction is high. These results suggest that lateral maneuvers may need other flight contextual information to explain and make predictions about them. The dependency test results in the option prediction are dependent on the type prediction. However, the type prediction is not affected by the results from its predecessor. However, it is inconclusive because significantly low performance on the type prediction could make the difference unable to detect clearly. Different flight contextual information played significant roles in each sub-model. It can imply that ATCos consider different information to make decisions when they are taking action on aircraft conflict pairs. Also, certain flight contextual information was playing significant roles across the different modeling methods. The altitude of the targeted aircraft affects predictions on vertical and speed option maneuvers. Checking current altitude to change the target's altitude can be both logical and operational explanation. Additionally, the aircraft's altitude affects the speed of aircraft due to the practical range of speed dependent on altitude, considering fuel consumption. However, this work does not conclude that ATCo utilizes such information for their actions because how they use the information is inconclusive. Based on the literature review, we only know that certain information affects their decisions. Due to the complexity in ATCo actions with multiple maneuvers, the prediction model was developed based on the actions with single maneuvers. Thus, the developed prediction model can be considered as a partial prediction model. The prediction model for those of the multiple maneuvers should be developed as future work. Lastly, the developed prediction model is limited to aircraft conflict pairs. There is a more sophisticated type of aircraft conflict that involves more than two aircraft. However, its input data is generated only for the conflict pairs.

Here are the final takeaways from this work. First, this work showed that we could generate human controls from the data. The developed methods and their results suggest a new approach to studies that their methods were limited to human subjective approaches. Additionally, this work shoed data-driven approach is more efficient than the conventional approaches in many ways. By utilizing current technologies, we can collect data in real-time and collect as much as possible. However, it does not mean that the data-driven approaches are superior so that the conventional approaches must be replaced. Knowledge about air traffic, flight operations, and ATCos from conventional studies enable the methods used in this work. Both methods have unique characteristics and should be applied for different purposes. Second, this study showed the importance of evaluating existing models. The results showed that the selected prediction model does not reflect the real-world. It warns us about both qualitative and quantitative risks of applying the unvalidated model to develop a critical system like air traffic control systems. Lastly, this study showed the relationship between flight contextual information and ATCo actions. It suggests a new path to develop high-end ATCo action prediction models with flight contextual information.

APPENDIX A
PART 1: SUPPLEMENTARY INFORMATION

This part of the Appendices includes supplementary information of Part 1. The data collection was reviewed by IRB due to the data resulting from humans (pilots), regardless of being trajectories of aircraft. A.1 shows approval from IRB that the data collection for Part 1 is exempted A.2 shows a sample of the open-loop data. The collected open-loop data is a series of codes that represent waypoints that aircraft should pass. They can be decoded to provide a type of waypoints and their coordinates. A.3 shows a sample of the closed-loop data. The closed-loop data includes the timestamp of each row to show when variables were recorded. The variables are coordinates, altitude, and speed. A.4 illustrates results from the deviation detection algorithm and its boxed region. The dotted line represents trajectories from the open-loop data, and the solid line is from the closed-loop data. The green lines represent deviations in the lateral dimension. A.5 illustrates results from the predicted conflict pair detection algorithm. The aircraft represented as blue color took a short-cut to avoid an aircraft in red color. A.6 lists identified predicted conflict pairs in tables. The unique flight ID of aircraft was shown in columns of AC1 and AC2. Aircraft correspond to AC1 are the targeted aircraft. The following 4 columns represent categorized ATCo actions. One in the target column represents that AC1 is closer to the conflict point and vice versa. The type column has three values; one represents lateral, two represents vertical, and three represents speed. One in the option column represents the details of the applied maneuver is categorized to be affecting the corresponding dimension in a positive way, and vice versa. The mix column represents whether the corresponding pair was resolved with single or multiple maneuvers. If the value is one, the following conflict pair has identical aircraft.

A.1 IRB Approval on the Data Collection

PURDUE
UNIVERSITY

HUMAN RESEARCH PROTECTION PROGRAM
INSTITUTIONAL REVIEW BOARDS

To:	LANDRY, STEVEN J
From:	DICLEMENTI, JEANNIE D, Chair Social Science IRB
Date:	01/11/2018
Committee Action:(4)	Determined Exempt, Category **(4)**
IRB Action Date:	01 / 11 / 2018
IRB Protocol #:	1801020078
Study Title:	Analysis Aircraft Conflict Resolution Actions from Recorded Air Transportation System

The Institutional Review Board (IRB) has reviewed the above-referenced study application and has determined that it meets the criteria for exemption under 45 CFR 46.101(b).

Before making changes to the study procedures, please submit an Amendment to ensure that the regulatory status of the study has not changed. Changes in key research personnel should also be submitted to the IRB through an amendment.

General

- To recruit from Purdue University classrooms, the instructor and all others associated with conduct of the course (e.g., teaching assistants) must not be present during announcement of the research opportunity or any recruitment activity. This may be accomplished by announcing, in advance, that class will either start later than usual or end earlier than usual so this activity may occur. It should be emphasized that attendance at the announcement and recruitment are voluntary and the student's attendance and enrollment decision will not be shared with those administering the course.
- If students earn extra credit towards their course grade through participation in a research project conducted by someone other than the course instructor(s), such as in the example above, the students participation should only be shared with the course instructor(s) at the end of the semester. Additionally, instructors who allow extra credit to be earned through participation in research must also provide an opportunity for students to earn comparable extra credit through a non-research activity requiring an amount of time and effort comparable to the research option.
- When conducting human subjects research at a non-Purdue college/university, investigators are urged to contact that institution's IRB to determine requirements for conducting research at that institution.
- When human subjects research will be conducted in schools or places of business, investigators must obtain written permission from an appropriate authority within the organization. If the written permission was not submitted with the study application at the time of IRB review (e.g., the school would not issue the letter without proof of IRB approval, etc.), the investigator must submit the written permission to the IRB prior to engaging in the research activities (e.g., recruitment, study procedures, etc.). Submit this documentation as an FYI through Coeus. This is an institutional requirement.

Categories 2 and 3

- Surveys and questionnaires should indicate
    - only participants 18 years of age and over are eligible to participate in the research; and
    - that participation is voluntary; and
    - that any questions may be skipped; and
    - include the investigator's name and contact information.
- Investigators should explain to participants the amount of time required to participate. Additionally, they should explain to participants how confidentiality will be maintained or if it will not be maintained.
- When conducting focus group research, investigators cannot guarantee that all participants in the focus group will maintain the confidentiality of other group participants. The investigator should make participants aware of this potential for breach of confidentiality.

Category 6

- Surveys and data collection instruments should note that participation is voluntary.
- Surveys and data collection instruments should note that participants may skip any questions.
- When taste testing foods which are highly allergenic (e.g., peanuts, milk, etc.) investigators should disclose the possibility of a reaction to potential subjects.

You are required to retain a copy of this letter for your records. We appreciate your commitment towards ensuring the ethical conduct of human subjects research and wish you luck with your study.

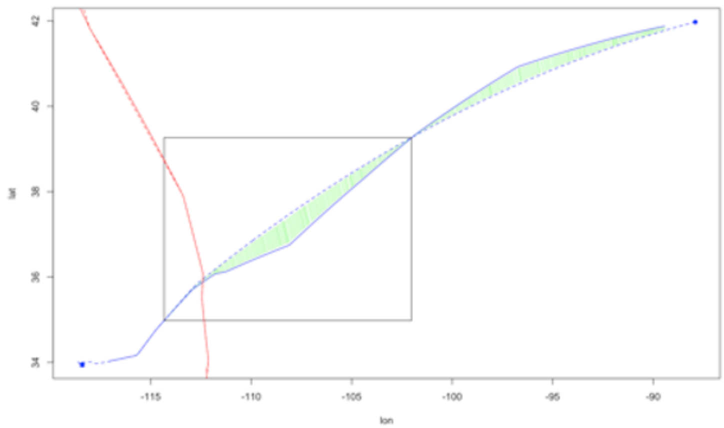
A.2 A Sample of the Open-Loop Data

name	type	lat	lon
KLAX	Origin Airport	33.94249	-118.408
CHVEZ	Waypoint	33.9945	-118.255
TRAAP	Waypoint	34.05833	-118.049
JIIVE	Waypoint	34.08972	-117.899
CLUTZ	Waypoint	34.18244	-117.703
GARDY	Reporting Point	34.25594	-117.548
ARCUS	Waypoint	34.54167	-117.102
YELAH	Waypoint	34.85417	-116.645
WYZEE	Waypoint	35.69608	-115.504
BEALE	Reporting Point	36.18244	-114.826
BAWER	WAY-PT	37.63519	-112.279
BUGGG	WAY-PT	38.65509	-109.497
DBL	VOR-DME (NAVAID)	39.43935	-106.895
DVV	VOR-TAC (NAVAID)	39.89469	-104.624
HCT	VOR-TAC (NAVAID)	40.45406	-100.924
OBH	VOR-TAC (NAVAID)	41.37574	-98.3536
FOD	VOR-TAC (NAVAID)	42.61111	-94.2947
KG75M	NRS-WAYPOINT	42.5	-88
DAFLU	Reporting Point	42.37908	-82.6888
BROKK	Reporting Point	42.33139	-81.5819
BEWEL	Reporting Point	42.28897	-80.7451
JHW	VOR-DME (NAVAID)	42.18861	-79.1213
HOXIE	Reporting Point	41.86501	-77.8526
DMACK	Reporting Point	41.78576	-77.5519
STENT	Reporting Point	41.67905	-77.1528
MAGIO	Reporting Point	41.52738	-76.5965
LVZ	VOR-TAC (NAVAID)	41.27281	-75.6895
JENNO	Reporting Point	41.15292	-75.3314
HARTY	Reporting Point	41.07119	-75.0899
MUGZY	Reporting Point	41.03014	-74.9694
STW	VOR-DME (NAVAID)	40.99583	-74.869
LENDY	Reporting Point	40.91483	-74.1353
LGA	VOR-DME (NAVAID)	40.78372	-73.8686
KJFK	Destination Airport	40.63993	-73.7787

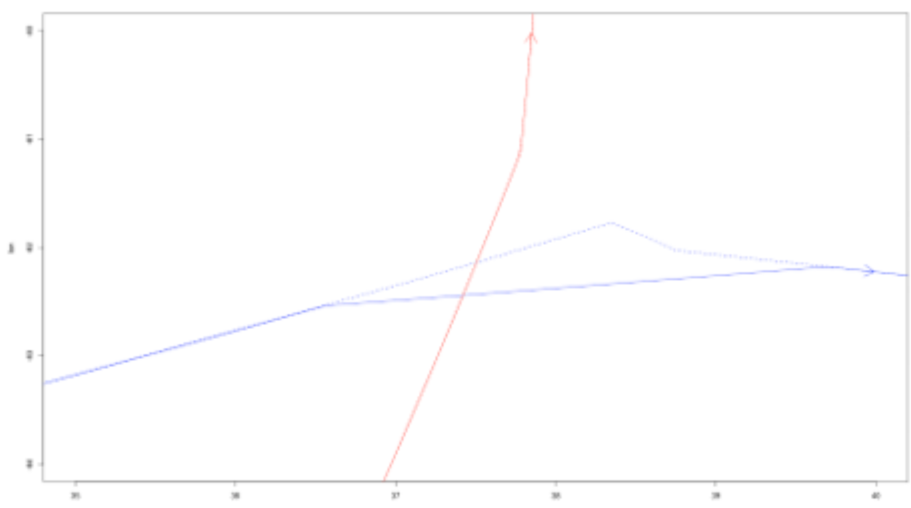
A.3 A Sample of the Closed-Loop Data

timestamp	lat	lon	spd	alt
1547572410	33.9522	-118.397	152	11
1547572426	33.9556	-118.385	151	17
1547572442	33.9596	-118.37	163	21
1547572458	33.9637	-118.356	183	24
1547572474	33.9684	-118.339	207	26
1547572499	33.9771	-118.309	246	30
1547572529	33.9886	-118.268	255	44
1547572550	33.9965	-118.241	263	53
1547572580	34.0111	-118.197	271	67
1547572610	34.0245	-118.156	278	78
1547572640	34.0381	-118.113	277	79
1547572670	34.0522	-118.068	279	80
1547572687	34.0594	-118.044	286	84
1547572714	34.0683	-118.003	291	94
1547572744	34.0783	-117.953	303	105
1547572771	34.0884	-117.906	328	111
1547572788	34.0984	-117.88	341	114
1547572818	34.1235	-117.828	369	120
1547572848	34.1504	-117.771	389	125
1547572878	34.1769	-117.715	398	136
1547572908	34.2051	-117.655	403	146
1547572938	34.2323	-117.598	403	157
1547572961	34.2554	-117.55	404	167

A.4 A Visualized Sample of the Deviation Detection



A.5 A Visualized Sample of the Predicted Aircraft Conflict Pair



A.6 The List of I identified Aircraft Conflict Pairs

A.6.1 Predicted Aircraft Conflicts of ZLA

ac1	ac2	target	type	option	mix
AAL1473-1547619949-airline-0240	AAL1165-1547619942-airline-0296	0	2	1	1
AAL1473-1547619949-airline-0240	AAL1165-1547619942-airline-0296	0	3	1	1
AAL1783-1547533573-airline-0204	AAL1156-1547533573-airline-0306	0	2	1	1
AAL1783-1547533573-airline-0204	AAL1156-1547533573-airline-0306	0	2	1	1
AAL1783-1547533573-airline-0204	AAL1156-1547533573-airline-0306	0	3	1	1
AAL1784-1547360814-airline-0209	AAL1235-1547360814-airline-0130	0	1	1	1
AAL1784-1547360814-airline-0209	AAL1235-1547360814-airline-0130	0	2	1	1
AAL1784-1547360814-airline-0209	AAL1235-1547360814-airline-0130	0	3	1	1
AAL1784-1547447160-airline-0058	AAL1163-1547447160-airline-0201	1	2	0	1
AAL1784-1547447160-airline-0058	AAL1163-1547447160-airline-0201	1	2	0	1
AAL1784-1547447160-airline-0481	AAL1161-1547447160-airline-0112	0	2	0	1
AAL1784-1547447160-airline-0481	AAL1161-1547447160-airline-0112	1	3	0	1
AAL1784-1547533573-airline-0173	AAL1161-1547533573-airline-0407	1	2	0	0
AAL1799-1547360814-airline-0231	AAL1235-1547360814-airline-0130	1	2	1	1
AAL1799-1547360814-airline-0231	AAL1235-1547360814-airline-0130	1	3	1	1
AAL1799-1547360814-airline-0231	AAL1235-1547360814-airline-0130	1	3	0	1
AAL1799-1547360814-airline-0231	AAL1473-1547360821-airline-0094	1	2	0	0
AAL1799-1547619942-airline-0205	AAL1235-1547619942-airline-0114	0	3	1	0

ac1	ac2	target	type	option	mix
AAL1868-1547360814-airline-0358	AAL1472-1547360814-airline-0207	0	1	1	1
AAL1868-1547360814-airline-0358	AAL1472-1547360814-airline-0207	0	2	1	1
AAL1868-1547360814-airline-0358	AAL1472-1547360814-airline-0207	0	3	1	1
AAL2045-1547360814-airline-0074	AAL1401-1547360814-airline-0084	1	2	1	1
AAL2045-1547360814-airline-0074	AAL1401-1547360814-airline-0084	1	3	1	1
AAL2215-1547274356-airline-0175	AAL1470-1547274356-airline-0356	1	3	0	0
AAL2225-1547447160-airline-0424	AAL1402-1547447160-airline-0420	1	1	1	1
AAL2225-1547447160-airline-0424	AAL1402-1547447160-airline-0420	1	3	0	1
AAL231-1547360814-airline-0315	AAL1402-1547360814-airline-0560	0	2	1	0
AAL236-1547619942-airline-0508	AAL1235-1547619942-airline-0114	1	3	0	0
AAL2361-1547360820-airline-0142	AAL1472-1547360814-airline-0116	1	3	0	0
AAL2452-1547360814-airline-0412	AAL1081-1547360814-airline-0288	0	3	0	0
AAL2546-1547360814-airline-0349	AAL1472-1547360814-airline-0207	1	2	0	0
AAL2546-1547533573-airline-0576	AAL1402-1547533573-airline-0274	1	2	1	1
AAL2546-1547533573-airline-0576	AAL1402-1547533573-airline-0274	0	2	0	1
AAL255-1547360820-airline-0408	AAL1473-1547360821-airline-0094	1	1	0	0
AAL255-1547447160-airline-0427	AAL1163-1547447160-airline-0201	1	1	0	1
AAL255-1547447160-airline-0427	AAL1163-1547447160-airline-0201	0	3	1	1
AAL2680-1547360814-airline-0291	AAL1388-1547360814-airline-0474	0	1	1	0

ac1	ac2	target	type	option	mix
AAL2680-1547360814-airline-0449	AAL1401-1547360814-airline-0084	1	3	0	0
AAL2680-1547447160-airline-0637	AAL1388-1547447160-airline-0371	0	1	0	1
AAL2680-1547447160-airline-0637	AAL1388-1547447160-airline-0371	1	1	0	1
AAL2680-1547447160-airline-0637	AAL1388-1547447160-airline-0371	0	3	1	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	0	1	0	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	0	1	1	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	0	1	1	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	1	2	1	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	0	2	0	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	1	3	1	1
AAL2797-1547360814-airline-0555	AAL1004-1547360814-airline-0412	0	3	0	1
AAL314-1547619942-airline-0088	AAL1716-1547619942-airline-0203	0	1	0	1
AAL314-1547619942-airline-0088	AAL1716-1547619942-airline-0203	0	2	1	1
AAL314-1547619942-airline-0088	AAL1716-1547619942-airline-0203	1	3	0	1
AAL314-1547619942-airline-0088	AAL1716-1547619942-airline-0203	1	3	1	1
AAL362-1547447160-airline-0572	AAL102-1547360814-airline-0460	1	2	0	0
AAL362-1547447160-airline-0572	AAL116-1547360814-airline-0485	1	2	0	0
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	1	2	1	1
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	1	2	1	1

ac1	ac2	target	type	option	mix
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	0	2	0	1
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	0	2	1	1
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	0	2	0	1
AAL362-1547619942-airline-0193	AAL1004-1547619942-airline-0573	1	3	1	1
AAL384-1547360814-airline-0649	AAL1386-1547360814-airline-0526	0	3	0	0
AAL42-1547447160-airline-0437	AAL1472-1547447160-airline-0155	0	1	1	1
AAL42-1547447160-airline-0437	AAL1472-1547447160-airline-0155	0	2	0	1
AAL42-1547533573-airline-0245	AAL1163-1547533573-airline-0148	0	2	0	0
AAL53-1547533573-airline-0265	AAL1386-1547533573-airline-0007	0	1	0	0
AAL546-1547274356-airline-0081	AAL1401-1547274356-airline-0371	0	2	1	0
AAL547-1547274356-airline-0250	AAL1156-1547274356-airline-0450	0	2	1	0
AAL547-1547274356-airline-0250	AAL1386-1547274356-airline-0059	1	1	1	0
AAL547-1547533573-airline-0051	AAL1386-1547533573-airline-0267	0	2	1	0
AAL552-1547447160-airline-0640	AAL1472-1547447160-airline-0155	1	2	0	0
AAL566-1547360814-airline-0516	AAL152-1547360814-airline-0261	1	3	0	0
AAL566-1547619943-airline-0492	AAL1235-1547619942-airline-0114	1	2	1	0
AAL698-1547274356-airline-0010	AAL1386-1547274356-airline-0059	1	1	1	1
AAL698-1547274356-airline-0010	AAL1386-1547274356-airline-0059	1	2	0	1
AAL880-1547619943-airline-0023	AAL102-1547533573-airline-0078	1	1	0	1

ac1	ac2	target	type	option	mix
AAL880-1547619943-airline-0023	AAL102-1547533573-airline-0078	1	3	0	1
AAL880-1547619943-airline-0023	AAL116-1547533573-airline-0090	0	1	1	1
AAL880-1547619943-airline-0023	AAL116-1547533573-airline-0090	0	3	0	1
AAL880-1547619943-airline-0023	AAL152-1547619942-airline-0559	1	1	0	0
AAY20-1547533578-airline-0326	AAL1386-1547533573-airline-0007	1	3	0	0
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	2	0	1
AAY702-1547533578-airline-0178	AAL1402-1547533573-airline-0274	1	3	0	1
ACA1055-1547619943-airline-0423	AAL1473-1547619949-airline-0240	1	3	0	0
ACA1057-1547533573-airline-0347	AAL1386-1547533573-airline-0007	1	2	0	0
ACA794-1547619943-airline-0065	AAL1716-1547619942-airline-0203	0	2	1	1
ACA794-1547619943-airline-0065	AAL1716-1547619942-airline-0203	1	3	0	1

ac1	ac2	target	type	option	mix
ACA796-1547533573-airline-0124	AAL1386-1547533573-airline-0007	1	2	0	0
ACA797-1547533573-airline-0264	AAL1235-1547533573-airline-0367	1	1	0	0
ACA799-1547360814-airline-0017	AAL1235-1547360814-airline-0130	1	2	1	0
AFL107-1547533583-airline-0270	AAL1386-1547533573-airline-0007	1	1	0	0
ASA1399-1547447161-airline-0253	AAL1163-1547447160-airline-0201	0	2	0	1
ASA1399-1547447161-airline-0253	AAL1163-1547447160-airline-0201	0	3	0	1
ASA1399-1547447161-airline-0253	AAL1472-1547447160-airline-0155	0	2	0	1
ASA1399-1547447161-airline-0253	AAL1472-1547447160-airline-0155	0	3	0	1
ASA1413-1547360815-airline-0012	AAL1386-1547360814-airline-0526	1	3	0	0
ASA315-1547360821-airline-0290	AAL1402-1547360814-airline-0560	1	2	0	1
ASA315-1547360821-airline-0290	AAL1402-1547360814-airline-0560	1	3	0	1
ASA315-1547533574-airline-0109	AAL1402-1547533573-airline-0274	0	2	1	1
ASA315-1547533574-airline-0109	AAL1402-1547533573-airline-0274	1	3	0	1
ASA315-1547533574-airline-0109	AAL1402-1547533573-airline-0274	1	3	0	1
ASA608-1547274358-airline-0132	AAL1004-1547360814-airline-0412	0	1	1	1
ASA608-1547274358-airline-0132	AAL1004-1547360814-airline-0412	0	2	0	1
ASA608-1547274358-airline-0132	AAL1004-1547360814-airline-0412	0	3	0	1
ASA626-1547533574-airline-0088	AAL1402-1547533573-airline-0274	0	1	1	1
ASA626-1547533574-airline-0088	AAL1402-1547533573-airline-0274	0	2	1	1

ac1	ac2	target	type	option	mix
ASA626-1547533574-airline-0088	AAL1402-1547533573-airline-0274	0	3	1	1
ASA626-1547533574-airline-0088	AAL1402-1547533573-airline-0274	0	3	1	1
ASA633-1547274358-airline-0182	AAL1386-1547274356-airline-0234	1	1	0	1
ASA633-1547274358-airline-0182	AAL1386-1547274356-airline-0234	1	2	0	1
ASH5869-1547619943-airline-0117	AAL1235-1547619942-airline-0114	0	3	0	0
CPA881-1547360817-airline-0063	AAL1405-1547447160-airline-0345	1	2	0	1
CPA881-1547360817-airline-0063	AAL1405-1547447160-airline-0345	1	3	0	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	0	1	0	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	1	1	0	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	1	1	0	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	0	2	1	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	1	2	0	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	0	3	1	1
CPZ5720-1547533585-airline-0106	AAL1472-1547533573-airline-0036	1	3	0	1
CPZ6052-1547274356-airline-0284	AAL1470-1547274356-airline-0356	0	1	0	0
CPZ6052-1547360825-airline-0118	AAL1470-1547360814-airline-0078	1	1	0	0
DAL1053-1547274359-airline-0360	AAL1386-1547274356-airline-0059	1	2	1	0
DAL1215-1547447163-airline-0055	AAL1401-1547447160-airline-0041	0	2	1	1
DAL1215-1547447163-airline-0055	AAL1401-1547447160-airline-0041	0	3	0	1

ac1	ac2	target	type	option	mix
DAL1217-1547274359-airline-0152	AAL1386-1547274356-airline-0234	0	1	1	1
DAL1217-1547274359-airline-0152	AAL1386-1547274356-airline-0234	0	2	1	1
DAL1217-1547274359-airline-0152	AAL1386-1547274356-airline-0234	0	2	0	1
DAL1217-1547274359-airline-0152	AAL1386-1547274356-airline-0234	0	3	0	1
DAL1217-1547533576-airline-0160	AAL1386-1547533573-airline-0267	1	1	0	1
DAL1217-1547533576-airline-0160	AAL1386-1547533573-airline-0267	1	3	0	1
DAL1222-1547447163-airline-0108	AAL1472-1547447160-airline-0155	1	2	1	0
DAL1238-1547533576-airline-0046	AAL1235-1547533573-airline-0367	1	2	0	0
DAL1243-1547619946-airline-0233	AAL102-1547533573-airline-0078	1	1	1	0
DAL1287-1547360817-airline-0465	AAL1386-1547360814-airline-0526	0	1	1	1
DAL1287-1547360817-airline-0465	AAL1386-1547360814-airline-0526	0	2	0	1
DAL1331-1547619946-airline-0064	AAL1004-1547619942-airline-0573	1	1	1	1
DAL1331-1547619946-airline-0064	AAL1004-1547619942-airline-0573	1	2	0	1
DAL1331-1547619946-airline-0064	AAL1004-1547619942-airline-0573	0	2	0	1
DAL1331-1547619946-airline-0064	AAL1004-1547619942-airline-0573	0	2	0	1
DAL1331-1547619946-airline-0064	AAL1004-1547619942-airline-0573	1	3	1	1
DAL1366-1547360817-airline-0191	AAL1386-1547360814-airline-0526	1	2	0	1
DAL1366-1547360817-airline-0191	AAL1386-1547360814-airline-0526	1	3	0	1
DAL1372-1547274359-airline-0018	AAL1386-1547274356-airline-0234	0	1	1	0

ac1	ac2	target	type	option	mix
DAL1446-1547360817-airline-0201	AAL1386-1547360814-airline-0526	0	2	0	0
DAL1446-1547533576-airline-0223	AAL1386-1547533573-airline-0267	0	3	1	0
DAL1447-1547360817-airline-0462	AAL1472-1547360814-airline-0207	0	1	1	1
DAL1447-1547360817-airline-0462	AAL1472-1547360814-airline-0207	0	2	0	1
DAL1447-1547447163-airline-0313	AAL1472-1547447160-airline-0155	1	1	0	0
DAL1531-1547360817-airline-0481	AAL1235-1547360814-airline-0130	1	1	0	0
DAL1531-1547619946-airline-0431	AAL1473-1547619949-airline-0240	0	3	0	0
DAL1538-1547360817-airline-0464	AAL1472-1547360814-airline-0207	1	1	0	1
DAL1538-1547360817-airline-0464	AAL1472-1547360814-airline-0207	1	1	0	1
DAL1538-1547360817-airline-0464	AAL1472-1547360814-airline-0207	1	2	1	1
DAL1538-1547360817-airline-0464	AAL1472-1547360814-airline-0207	1	3	1	1
DAL1538-1547360817-airline-0464	AAL1472-1547360814-airline-0207	1	3	0	1
DAL1842-1547447163-airline-0093	AAL1402-1547447160-airline-0420	1	2	0	1
DAL1842-1547447163-airline-0093	AAL1402-1547447160-airline-0420	0	2	0	1
DAL1842-1547533576-airline-0422	AAL1156-1547533573-airline-0306	1	2	0	0
DAL1847-1547533576-airline-0346	AAL1386-1547533573-airline-0007	1	2	0	0
DAL1862-1547360817-airline-0559	AAL1156-1547360814-airline-0256	1	3	0	0
DAL1929-1547360817-airline-0079	AAL1402-1547360814-airline-0560	0	1	1	0
DAL2505-1547447163-airline-0039	AAL1402-1547447160-airline-0420	0	2	0	0

ac1	ac2	target	type	option	mix
DAL2657-1547360817-airline-0211	AAL1401-1547360814-airline-0084	0	1	1	1
DAL2657-1547360817-airline-0211	AAL1401-1547360814-airline-0084	0	1	1	1
DAL2657-1547360817-airline-0211	AAL1401-1547360814-airline-0084	0	2	1	1
DAL2657-1547360817-airline-0211	AAL1401-1547360814-airline-0084	0	2	1	1
DAL2657-1547360817-airline-0211	AAL1401-1547360814-airline-0084	0	3	1	1
DAL2664-1547360817-airline-0589	AAL1081-1547360814-airline-0288	0	1	0	1
DAL2664-1547360817-airline-0589	AAL1081-1547360814-airline-0288	0	2	1	1
DAL2894-1547619946-airline-0380	AAL1165-1547619942-airline-0296	0	1	1	1
DAL2894-1547619946-airline-0380	AAL1165-1547619942-airline-0296	0	2	1	1
DAL2894-1547619946-airline-0380	AAL1165-1547619942-airline-0296	0	3	1	1
DAL468-1547533576-airline-0534	AAL1386-1547533573-airline-0007	1	1	0	0
DAL546-1547360817-airline-0291	AAL1235-1547360814-airline-0130	1	1	0	1
DAL546-1547360817-airline-0291	AAL1235-1547360814-airline-0130	1	2	0	1
DAL78-1547274359-airline-0033	AAL1401-1547274356-airline-0371	1	3	0	0
DAL781-1547533576-airline-0138	AAL1386-1547533573-airline-0267	0	1	0	0
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	1	0	1
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	1	0	1
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	1	1	1
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	2	1	1

ac1	ac2	target	type	option	mix
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	2	0	1
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	3	1	1
DPJ785-1547566652-dlad-6213894	AAL1472-1547447160-airline-0155	1	3	0	1
EJA555-1547679948-0-0-103	AAL1386-1547533573-airline-0007	1	3	0	0
FDX1026-1547709509-0-2-183	AAL102-1547533573-airline-0078	1	1	1	0
FDX1167-1547462907-0-4-51	AAL1004-1547360814-airline-0412	1	3	0	0
FDX1438-1547720345-1-1-18	AAL1004-1547619942-airline-0573	1	3	1	0
FDX1508-1547549343-0-0-72	AAL102-1547360814-airline-0460	1	3	0	0
FDX1508-1547549343-0-0-72	AAL116-1547360814-airline-0485	1	3	0	0
FDX1560-1547471897-21-1-118	AAL1405-1547360814-airline-0504	1	3	0	0
FDX1566-1547545707-25-1-124	AAL1153-1547447160-airline-0236	1	1	0	0
FDX1748-1547720323-1-0-20	AAL102-1547533573-airline-0078	1	1	1	1
FDX1748-1547720323-1-0-20	AAL102-1547533573-airline-0078	1	2	1	1
FDX3022-1547572710-3-0-137	AAL1161-1547447160-airline-0112	0	2	1	0
FDX451-1547561943-0-1-218	AAL1153-1547447160-airline-0236	0	3	0	0
FDX749-1547504333-1-1-210	AAL1401-1547360814-airline-0084	1	1	1	0
FDX839-1547736523-6-0-32	AAL1472-1547619942-airline-0115	1	3	0	0
FDX978-1547588901-0-0-148	AAL1401-1547447160-airline-0041	1	2	0	1
FDX978-1547588901-0-0-148	AAL1401-1547447160-airline-0041	1	2	1	1

ac1	ac2	target	type	option	mix
FFT1062-1547360819-airline-0129	AAL1402-1547360814-airline-0560	1	1	1	0
FFT1062-1547533577-airline-0084	AAL1401-1547533573-airline-0191	0	2	1	1
FFT1062-1547533577-airline-0084	AAL1401-1547533573-airline-0191	0	3	0	1
FFT1062-1547533577-airline-0084	AAL1402-1547533573-airline-0274	1	2	1	0
FFT710-1547533577-airline-0160	AAL1386-1547533573-airline-0007	1	2	1	1
FFT710-1547533577-airline-0160	AAL1386-1547533573-airline-0007	1	3	0	1
FFT87-1547533577-airline-0074	AAL1386-1547533573-airline-0007	1	2	0	1
FFT87-1547533577-airline-0074	AAL1386-1547533573-airline-0007	1	3	0	1
FLE765-1547533577-airline-0265	AAL1386-1547533573-airline-0267	0	3	0	0
GAJ14-1547581190-dlad-6214436	AAL1401-1547447160-airline-0041	0	3	0	0
GTI3078-1547574598-3-0-248	AAL1472-1547360814-airline-0207	1	1	1	0
JBU1623-1547533574-airline-0027	AAL1386-1547533573-airline-0267	0	3	0	0
JBU167-1547274358-airline-0265	AAL1386-1547274356-airline-0234	0	2	0	0
JBU178-1547533574-airline-0468	AAL1470-1547533573-airline-0279	1	1	0	1
JBU178-1547533574-airline-0468	AAL1470-1547533573-airline-0279	1	2	0	1
JBU323-1547360816-airline-0066	AAL1473-1547360821-airline-0094	1	2	0	0
JBU323-1547447162-airline-0135	AAL1163-1547447160-airline-0201	1	1	0	1
JBU323-1547447162-airline-0135	AAL1163-1547447160-airline-0201	0	3	0	1
JBU323-1547533574-airline-0089	AAL1401-1547533573-airline-0191	1	1	0	1

ac1	ac2	target	type	option	mix
JBU323-1547533574-airline-0089	AAL1401-1547533573-airline-0191	1	2	1	1
JBU405-1547274358-airline-0067	AAL1386-1547274356-airline-0234	0	3	0	0
JBU405-1547360816-airline-0346	AAL1386-1547360814-airline-0526	1	2	0	0
JTL602-1547591240-dlad-6214773	AAL1235-1547447160-airline-0333	1	3	1	0
KAL17-1547616600-schedule-0000	AAL1235-1547619942-airline-0114	0	1	0	1
KAL17-1547616600-schedule-0000	AAL1235-1547619942-airline-0114	0	2	0	1
KAL31-1547428800-schedule-0001	AAL102-1547360814-airline-0460	0	3	0	0
KAL31-1547428800-schedule-0001	AAL116-1547360814-airline-0485	0	3	0	0
KFS726-1547640803-1-0-161	AAL1235-1547447160-airline-0333	1	3	0	0
LXJ532-1547775988-8-0-90	AAL1473-1547619949-airline-0240	0	2	0	1
LXJ532-1547775988-8-0-90	AAL1473-1547619949-airline-0240	0	3	0	1
N167AA-1547524797-1-0-32	AAL1402-1547360814-airline-0560	0	1	1	1
N167AA-1547524797-1-0-32	AAL1402-1547360814-airline-0560	0	2	0	1
N167AA-1547524797-1-0-32	AAL1402-1547360814-airline-0560	0	3	0	1
N25MX-1547679487-0-1-32	AAL1235-1547533573-airline-0367	1	3	0	0
N562BC-1547634765-1-2-132	AAL1235-1547447160-airline-0333	1	2	0	0
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	1	1	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	1	1	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	1	1

ac1	ac2	target	type	option	mix
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	1	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	2	0	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	3	1	1
N712WB-1547657002-6-0-47	AAL1472-1547447160-airline-0155	0	3	1	1
N82FB-1547647357-2-1-78	AAL1077-1547447160-airline-0045	1	1	1	0
N900D-1547735590-1-0-199	AAL1161-1547533573-airline-0407	1	2	0	1
N900D-1547735590-1-0-199	AAL1161-1547533573-airline-0407	1	2	0	1
N900D-1547735590-1-0-199	AAL1161-1547533573-airline-0407	0	2	0	1
N91CH-1547566348-6-0-205	AAL1235-1547360814-airline-0130	1	2	1	1
N91CH-1547566348-6-0-205	AAL1235-1547360814-airline-0130	1	3	0	1
N993SJ-1547554498-12-1-54	AAL1235-1547360814-airline-0130	1	2	0	0
QFA11-1547619952-airline-0362	AAL1473-1547619949-airline-0240	1	3	1	0
QFA12-1547533581-airline-0171	AAL1386-1547533573-airline-0007	0	1	1	0

ac1	ac2	target	type	option	mix
ROU1826-1547274356-airline-0136	AAL1156-1547274356-airline-0450	1	1	0	0
SKW3348-1547491863-33-1-169	AAL1386-1547274356-airline-0059	0	1	1	0
SKW3658-1547360826-airline-0001	AAL1472-1547360814-airline-0207	1	1	1	1
SKW3658-1547360826-airline-0001	AAL1472-1547360814-airline-0207	1	2	1	1
SKW3658-1547360826-airline-0001	AAL1472-1547360814-airline-0207	1	3	1	1
SKW3658-1547447161-airline-0104	AAL1472-1547447160-airline-0155	0	3	1	0
SKW3658-1547533576-airline-0471	AAL1473-1547533579-airline-0382	1	1	0	1
SKW3658-1547533576-airline-0471	AAL1473-1547533579-airline-0382	1	2	1	1
SKW3658-1547533576-airline-0471	AAL1473-1547533579-airline-0382	1	2	0	1
SKW3658-1547533576-airline-0471	AAL1473-1547533579-airline-0382	1	3	1	1
SKW3658-1547533576-airline-0471	AAL1473-1547533579-airline-0382	1	3	0	1
SKW5215-1547447171-airline-0068	AAL152-1547447160-airline-0250	1	1	0	0
SKW5215-1547619954-airline-0291	AAL152-1547619942-airline-0559	1	3	1	0
SKW5519-1547274364-airline-0108	AAL1161-1547274356-airline-0455	0	3	0	0
SKW5519-1547533575-airline-0075	AAL1161-1547533573-airline-0407	1	1	0	1
SKW5519-1547533575-airline-0075	AAL1161-1547533573-airline-0407	1	3	1	1
SKW5523-1547533584-airline-0171	AAL1386-1547533573-airline-0267	0	3	1	0
SKW5994-1547447160-airline-0249	AAL1235-1547447160-airline-0333	1	2	0	0
SPA709-1547562512-7-0-26	AAL1472-1547360814-airline-0207	0	3	1	0

ac1	ac2	target	type	option	mix
SWA1012-1547619955-airline-0617	AAL1473-1547619949-airline-0240	1	2	0	0
SWA104-1547447172-airline-0748	AAL152-1547447160-airline-0250	1	2	1	0
SWA106-1547360826-airline-0845	AAL1402-1547360814-airline-0560	0	3	1	0
SWA106-1547447172-airline-0408	AAL1402-1547447160-airline-0420	0	1	1	1
SWA106-1547447172-airline-0408	AAL1402-1547447160-airline-0420	0	2	1	1
SWA106-1547447172-airline-0408	AAL1402-1547447160-airline-0420	1	3	1	1
SWA106-1547533585-airline-0338	AAL1472-1547533573-airline-0036	1	2	0	0
SWA1060-1547533585-airline-0267	AAL1402-1547533573-airline-0274	1	2	0	0
SWA117-1547360826-airline-0416	AAL1472-1547360814-airline-0207	0	1	0	0
SWA1222-1547274368-airline-0786	AAL1386-1547274356-airline-0234	0	1	1	1
SWA1222-1547274368-airline-0786	AAL1386-1547274356-airline-0234	0	2	1	1
SWA1303-1547274368-airline-0292	AAL1386-1547274356-airline-0234	1	2	0	0
SWA1321-1547533585-airline-0544	AAL1386-1547533573-airline-0267	0	3	1	0
SWA1322-1547447172-airline-0665	AAL1472-1547447160-airline-0520	0	3	1	0
SWA1381-1547274368-airline-0589	AAL1470-1547274356-airline-0322	0	3	1	0
SWA1458-1547447172-airline-0704	AAL1077-1547447160-airline-0045	1	3	0	0
SWA1458-1547447172-airline-0704	AAL1235-1547447160-airline-0333	1	1	0	0
SWA1458-1547619955-airline-0296	AAL1077-1547619942-airline-0533	1	3	0	0
SWA1690-1547447172-airline-0262	AAL102-1547360814-airline-0460	1	3	0	0

ac1	ac2	target	type	option	mix
SWA1690-1547447172-airline-0262	AAL116-1547360814-airline-0485	1	3	0	0
SWA2031-1547274368-airline-1029	AAL1386-1547274356-airline-0059	1	3	0	0
SWA2045-1547533585-airline-0774	AAL1235-1547533573-airline-0367	1	1	0	0
SWA2045-1547619955-airline-0573	AAL1235-1547619942-airline-0114	1	1	0	0
SWA2111-1547274368-airline-0811	AAL1386-1547274356-airline-0059	1	1	0	1
SWA2111-1547274368-airline-0811	AAL1386-1547274356-airline-0059	1	3	0	1
SWA2111-1547533585-airline-0871	AAL1386-1547533573-airline-0007	1	2	1	0
SWA2113-1547447172-airline-0987	AAL1077-1547447160-airline-0045	1	3	1	0
SWA2113-1547447172-airline-0987	AAL1235-1547447160-airline-0333	1	3	1	0
SWA2113-1547619955-airline-0319	AAL1473-1547619949-airline-0240	1	1	0	1
SWA2113-1547619955-airline-0319	AAL1473-1547619949-airline-0240	1	3	1	1
SWA259-1547619955-airline-0780	AAL1716-1547619942-airline-0203	1	1	0	1
SWA259-1547619955-airline-0780	AAL1716-1547619942-airline-0203	0	2	0	1
SWA259-1547619955-airline-0780	AAL1716-1547619942-airline-0203	0	3	0	1
SWA32-1547619955-airline-0262	AAL1792-1547619942-airline-0159	1	2	0	0
SWA422-1547360826-airline-0375	AAL1401-1547360814-airline-0084	1	3	0	0
SWA424-1547533585-airline-0717	AAL1386-1547533573-airline-0007	1	3	1	0
SWA442-1547274368-airline-0557	AAL1401-1547274356-airline-0371	0	2	0	1
SWA442-1547274368-airline-0557	AAL1401-1547274356-airline-0371	0	3	0	1

ac1	ac2	target	type	option	mix
SWA490-1547447172-airline-0820	AAL1077-1547447160-airline-0045	1	1	0	1
SWA490-1547447172-airline-0820	AAL1077-1547447160-airline-0045	0	2	1	1
SWA490-1547447172-airline-0820	AAL1077-1547447160-airline-0045	1	2	0	1
SWA490-1547447172-airline-0820	AAL1077-1547447160-airline-0045	0	3	1	1
SWA490-1547447172-airline-0820	AAL1077-1547447160-airline-0045	1	3	1	1
SWA491-1547447172-airline-0718	AAL1153-1547447160-airline-0236	1	1	0	0
SWA493-1547619955-airline-0027	AAL1077-1547619942-airline-0533	1	2	0	0
SWA494-1547533585-airline-0399	AAL1491-1547533573-airline-0619	0	2	1	1
SWA494-1547533585-airline-0399	AAL1491-1547533573-airline-0619	0	3	1	1
SWA5651-1547447172-airline-0059	AAL1163-1547447160-airline-0201	1	1	1	0
SWA575-1547274368-airline-0528	AAL1386-1547274356-airline-0234	0	3	0	0
SWA575-1547447172-airline-0217	AAL1077-1547447160-airline-0045	0	2	1	1
SWA575-1547447172-airline-0217	AAL1077-1547447160-airline-0045	0	3	1	1
SWA575-1547447172-airline-0217	AAL1077-1547447160-airline-0045	1	3	0	1
SWA575-1547447172-airline-0217	AAL1077-1547447160-airline-0045	0	3	0	1
SWA575-1547533585-airline-0366	AAL1386-1547533573-airline-0267	0	1	0	0
SWA652-1547533585-airline-0406	AAL1161-1547533573-airline-0407	1	1	0	1
SWA652-1547533585-airline-0406	AAL1161-1547533573-airline-0407	1	2	1	1
SWA756-1547360826-airline-0057	AAL152-1547360814-airline-0261	0	1	1	1

ac1	ac2	target	type	option	mix
SWA756-1547360826-airline-0057	AAL152-1547360814-airline-0261	0	1	1	1
SWA756-1547360826-airline-0057	AAL152-1547360814-airline-0261	0	2	1	1
SWA756-1547360826-airline-0057	AAL152-1547360814-airline-0261	0	3	1	1
SWA818-1547533585-airline-0170	AAL1401-1547533573-airline-0191	1	1	0	0
SWA886-1547274368-airline-0006	AAL1401-1547274356-airline-0371	1	2	0	1
SWA886-1547274368-airline-0006	AAL1401-1547274356-airline-0371	0	3	0	1
SWG547-1547360826-airline-0284	AAL152-1547360814-airline-0261	0	3	0	0
UAL1213-1547273851-fa-0007	AAL1386-1547274356-airline-0059	1	3	0	0
UAL1213-1547273851-fa-0007	AAL1470-1547274356-airline-0356	1	1	0	0
UAL1213-1547534872-fa-0007	AAL1386-1547533573-airline-0267	0	3	0	0
UAL1430-1547274407-airline-0041	AAL116-1547274394-airline-0086	1	1	0	1
UAL1430-1547274407-airline-0041	AAL116-1547274394-airline-0086	1	2	1	1
UAL1537-1547360138-fa-0001	AAL1470-1547360814-airline-0046	0	2	1	1
UAL1537-1547360138-fa-0001	AAL1470-1547360814-airline-0046	0	3	0	1
UAL1678-1547533584-airline-0351	AAL1386-1547533573-airline-0007	1	3	0	0
UAL1731-1547533584-airline-0008	AAL102-1547533573-airline-0078	1	1	0	1
UAL1731-1547533584-airline-0008	AAL102-1547533573-airline-0078	1	1	0	1
UAL1731-1547533584-airline-0008	AAL102-1547533573-airline-0078	1	3	0	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	0	1	0	1

ac1	ac2	target	type	option	mix
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	1	1	0	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	0	1	0	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	1	1	0	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	0	2	1	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	0	3	1	1
UAL1731-1547533584-airline-0008	AAL116-1547533573-airline-0090	1	3	0	1
UAL1761-1547360825-airline-0037	AAL1402-1547360814-airline-0560	1	1	0	1
UAL1761-1547360825-airline-0037	AAL1402-1547360814-airline-0560	1	2	0	1
UAL1763-1547360825-airline-0019	AAL1081-1547360814-airline-0288	0	1	0	1
UAL1763-1547360825-airline-0019	AAL1081-1547360814-airline-0288	0	2	1	1
UAL1763-1547360825-airline-0019	AAL1081-1547360814-airline-0288	0	3	1	1
UAL2291-1547360825-airline-0298	AAL1004-1547360814-airline-0412	1	2	1	0
UAL407-1547445570-fa-0000	AAL1235-1547447160-airline-0333	1	1	0	1
UAL407-1547445570-fa-0000	AAL1235-1547447160-airline-0333	0	2	1	1
UAL407-1547445570-fa-0000	AAL1235-1547447160-airline-0333	1	2	1	1
UAL407-1547445570-fa-0000	AAL1235-1547447160-airline-0333	0	3	1	1
UAL407-1547445570-fa-0000	AAL1235-1547447160-airline-0333	1	3	1	1
UAL411-1547274367-airline-0132	AAL1156-1547274356-airline-0450	0	2	1	1
UAL411-1547274367-airline-0132	AAL1156-1547274356-airline-0450	0	3	1	1

ac1	ac2	target	type	option	mix
UAL497-1547447171-airline-0346	AAL1163-1547447160-airline-0201	0	3	0	0
UAL555-1547360825-airline-0270	AAL152-1547360814-airline-0261	0	1	1	1
UAL555-1547360825-airline-0270	AAL152-1547360814-airline-0261	1	2	1	1
UAL555-1547360825-airline-0270	AAL152-1547360814-airline-0261	1	3	1	1
UAL642-1547530675-fa-0002	AAL1491-1547533573-airline-0619	0	1	0	0
UAL788-1547447172-airline-0300	AAL1472-1547447160-airline-0520	1	3	0	1
UAL788-1547447172-airline-0300	AAL1472-1547447160-airline-0520	1	3	0	1
UAL788-1547533584-airline-0084	AAL1235-1547533573-airline-0367	0	1	1	0
UAL800-1547533584-airline-0078	AAL1470-1547533573-airline-0279	0	2	1	0
UAL810-1547533584-airline-0080	AAL1470-1547533573-airline-0279	0	2	1	1
UAL810-1547533584-airline-0080	AAL1470-1547533573-airline-0279	0	3	1	1
UPS2909-1547587959-3-0-24	AAL1153-1547447160-airline-0236	1	2	0	0
UPS2955-1547505459-2-1-65	AAL1163-1547360814-airline-0590	0	1	1	1
UPS2955-1547505459-2-1-65	AAL1163-1547360814-airline-0590	0	3	0	1
UPS2956-1547529460-0-1-66	AAL1388-1547360814-airline-0474	1	3	0	0
UPS808-1547747257-6-0-76	AAL1004-1547619942-airline-0573	1	1	0	1
UPS808-1547747257-6-0-76	AAL1004-1547619942-airline-0573	1	2	1	1
UPS808-1547747257-6-0-76	AAL1004-1547619942-airline-0573	1	3	1	1
UPS919-1547728357-8-0-167	AAL1061-1547533579-airline-0283	1	3	0	0

ac1	ac2	target	type	option	mix
VDA1607-1547565835-adhoc-0	AAL1077-1547360814-airline-0356	0	2	0	0
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	0	2	1	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	0	2	1	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	1	2	1	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	1	2	0	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	1	2	0	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	0	2	0	1
VDA1607-1547565835-adhoc-0	AAL1235-1547360814-airline-0130	1	3	0	1
VDA1607-1547565835-adhoc-0	AAL1402-1547360814-airline-0560	1	2	0	0
VIR7-1547360826-airline-0038	AAL152-1547360814-airline-0261	1	3	0	0
VIR7-1547447172-airline-0313	AAL1472-1547447160-airline-0155	0	1	1	0
VOI896-1547533586-airline-0131	AAL1386-1547533573-airline-0007	0	1	1	0
VOI899-1547360827-airline-0366	AAL1163-1547360814-airline-0590	1	2	0	0
VOI901-1547619955-airline-0120	AAL1405-1547629626-airline-0056	1	2	0	0
VOI939-1547360827-airline-0516	AAL1061-1547360821-airline-0207	1	2	1	1
VOI939-1547360827-airline-0516	AAL1061-1547360821-airline-0207	0	3	1	1
WCC48-1547762810-10-0-101	AAL1386-1547533573-airline-0007	1	1	0	1
WCC48-1547762810-10-0-101	AAL1386-1547533573-airline-0007	1	2	0	1
WJA1403-1547274368-airline-0154	AAL1401-1547274356-airline-0371	1	3	0	0

ac1	ac2	target	type	option	mix
WJA1474-1547533585-airline-0091	AAL1491-1547533573-airline-0619	0	2	1	0

A.6.2 Predicted Aircraft Conflicts of ZOB

ac1	ac2	target	type	option	mix
AAL2214-1547619942-airline-0291	AAL1403-1547619942-airline-0246	0	2	1	0
AAL230-1547533573-airline-0376	AAL1486-1547533573-airline-0364	0	2	1	1
AAL230-1547533573-airline-0376	AAL1486-1547533573-airline-0364	0	3	1	1
AAL233-1547533573-airline-0375	AAL1239-1547533573-airline-0241	1	2	1	0
AAL2369-1547619942-airline-0070	AAL1002-1547619942-airline-0011	1	2	1	0
AAL2506-1547533573-airline-0196	AAL1246-1547533579-airline-0289	0	1	1	0
AAL2521-1547360814-airline-0289	AAL1002-1547360814-airline-0430	1	3	0	0
AAL2527-1547619942-airline-0237	AAL1403-1547619942-airline-0246	1	1	0	1
AAL2527-1547619942-airline-0237	AAL1403-1547619942-airline-0246	1	3	0	1
AAL2676-1547619942-airline-0347	AAL1002-1547619942-airline-0011	0	3	1	0
AAL30-1547360814-airline-0113	AAL1239-1547360814-airline-0007	1	2	1	0
AAL52-1547533573-airline-0086	AAL1829-1547533573-airline-0217	1	2	0	1
AAL52-1547533573-airline-0086	AAL1829-1547533573-airline-0217	1	3	0	1
AAL552-1547360814-airline-0090	AAL1486-1547360814-airline-0154	0	1	1	0
AAL698-1547447160-airline-0047	AAL1492-1547447160-airline-0102	0	1	0	0
AAL703-1547274356-airline-0045	AAL1164-1547274356-airline-0307	0	2	1	0
AAL703-1547274356-airline-0045	AAL1246-1547274356-airline-0384	1	3	1	0
AAL703-1547533573-airline-0040	AAL1251-1547533573-airline-0395	1	2	1	1

ac1	ac2	target	type	option	mix
AAL703-1547533573-airline-0040	AAL1251-1547533573-airline-0395	1	2	1	1
AAL922-1547533573-airline-0079	AAL1246-1547533579-airline-0289	1	2	0	1
AAL922-1547533573-airline-0079	AAL1246-1547533579-airline-0289	1	3	0	1
AAL922-1547533573-airline-0079	AAL1246-1547533579-airline-0289	1	3	1	1
AAL922-1547533573-airline-0079	AAL1246-1547533579-airline-0289	1	3	0	1
ABX3430-1547661632-11-0-165	AAL1486-1547447160-airline-0145	1	3	0	0
ACA7081-1547597657-1-2-199	AAL1164-1547360814-airline-0373	1	1	0	0
ACA742-1547274356-airline-0244	AAL166-1547274356-airline-0132	1	1	0	0
ACA799-1547447160-airline-0344	AAL1239-1547447160-airline-0448	1	1	1	0
ACA799-1547447160-airline-0344	AAL1486-1547447160-airline-0145	1	3	0	0
ACA799-1547533573-airline-0193	AAL1239-1547533573-airline-0241	0	1	0	0
ACA881-1547360814-airline-0111	AAL1239-1547360814-airline-0007	0	2	0	1
ACA881-1547360814-airline-0111	AAL1239-1547360814-airline-0007	0	3	0	1
ACA881-1547360814-airline-0111	AAL1239-1547360814-airline-0007	0	3	0	1
ASA1011-1547447161-airline-0064	AAL1002-1547447160-airline-0048	1	2	0	0
ASA1011-1547447161-airline-0064	AAL1782-1547447160-airline-0523	1	2	0	0
ASA1024-1547360815-airline-0205	AAL1388-1547360814-airline-0474	0	1	1	1
ASA1024-1547360815-airline-0205	AAL1388-1547360814-airline-0474	0	2	0	1
ASA1024-1547360815-airline-0205	AAL1388-1547360814-airline-0474	0	3	1	1

ac1	ac2	target	type	option	mix
ASA1026-1547360815-airline-0072	AAL1246-1547360821-airline-0168	0	3	1	0
ASA1026-1547360815-airline-0072	AAL166-1547360814-airline-0284	0	2	0	0
ASA1084-1547360815-airline-0014	AAL1486-1547360814-airline-0154	0	2	0	1
ASA1084-1547360815-airline-0014	AAL1486-1547360814-airline-0154	0	3	0	1
ASA1084-1547447161-airline-0112	AAL1476-1547447160-airline-0028	0	2	1	1
ASA1084-1547447161-airline-0112	AAL1476-1547447160-airline-0028	0	2	1	1
ASA1084-1547447161-airline-0112	AAL1476-1547447160-airline-0028	0	3	1	1
ASA1089-1547619943-airline-0039	AAL1403-1547619942-airline-0246	1	3	0	0
ASA1166-1547274358-airline-0055	AAL1658-1547274356-airline-0628	0	1	0	1
ASA1166-1547274358-airline-0055	AAL1658-1547274356-airline-0628	1	2	0	1
ASA1166-1547274358-airline-0055	AAL1658-1547274356-airline-0628	1	2	0	1
ASA1166-1547274358-airline-0055	AAL1658-1547274356-airline-0628	1	3	0	1
ASA1166-1547274358-airline-0055	AAL1658-1547274356-airline-0628	1	3	0	1
ASA1413-1547533574-airline-0245	AAL1251-1547533573-airline-0395	1	3	0	0
ASA1416-1547533574-airline-0006	AAL1251-1547533573-airline-0395	0	2	0	0
ASA740-1547274358-airline-0027	AAL1164-1547274356-airline-0307	0	3	0	0
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	0	1	0	1
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	1	1	0	1
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	0	2	1	1

ac1	ac2	target	type	option	mix
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	0	3	1	1
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	1	3	0	1
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	1	3	0	1
ASH6286-1547619951-airline-0180	AAL1403-1547619942-airline-0246	1	3	0	1
ASH6366-1547274358-airline-0198	AAL1164-1547274356-airline-0307	1	2	1	1
ASH6366-1547274358-airline-0198	AAL1164-1547274356-airline-0307	1	3	1	1
ASQ4301-1547533573-airline-0255	AAL1239-1547533573-airline-0241	0	2	1	1
ASQ4301-1547533573-airline-0255	AAL1239-1547533573-airline-0241	0	3	1	1
ATN3804-1547554678-15-0-238	AAL1081-1547360814-airline-0288	0	1	1	1
ATN3804-1547554678-15-0-238	AAL1081-1547360814-airline-0288	0	2	1	1
ATN3804-1547641096-7-5-238	AAL1002-1547447160-airline-0048	1	3	0	0
AWI4823-1547274356-airline-0005	AAL1246-1547274356-airline-0384	0	1	1	1
AWI4823-1547274356-airline-0005	AAL1246-1547274356-airline-0384	0	2	0	1
AWI4823-1547274356-airline-0005	AAL1246-1547274356-airline-0384	0	3	1	1
DAL1443-1547274359-airline-0338	AAL1246-1547274356-airline-0384	1	2	0	1
DAL1443-1547274359-airline-0338	AAL1246-1547274356-airline-0384	1	2	0	1
DAL1443-1547274359-airline-0338	AAL1246-1547274356-airline-0384	0	2	0	1
DAL1443-1547360817-airline-0141	AAL1246-1547360821-airline-0168	0	1	1	0
DAL1762-1547447163-airline-0531	AAL1002-1547447160-airline-0048	1	1	1	1

ac1	ac2	target	type	option	mix
DAL1762-1547447163-airline-0531	AAL1002-1547447160-airline-0048	1	2	1	1
DAL1762-1547447163-airline-0531	AAL1002-1547447160-airline-0048	1	3	1	1
DAL1762-1547447163-airline-0531	AAL1476-1547447160-airline-0028	1	3	0	0
DAL1862-1547533576-airline-0334	AAL1829-1547533573-airline-0217	0	1	1	0
DAL1872-1547274359-airline-0203	AAL1486-1547274356-airline-0544	0	1	1	0
DAL1907-1547360817-airline-0130	AAL1246-1547360821-airline-0168	0	3	0	0
DAL1924-1547533576-airline-0132	AAL1640-1547533573-airline-0272	0	1	1	1
DAL1924-1547533576-airline-0132	AAL1640-1547533573-airline-0272	0	2	1	1
DAL2032-1547447163-airline-0451	AAL1002-1547447160-airline-0048	1	2	0	0
DAL2109-1547274359-airline-0572	AAL1486-1547274356-airline-0544	0	1	1	0
DAL2109-1547447163-airline-0194	AAL1476-1547447160-airline-0028	1	1	1	1
DAL2109-1547447163-airline-0194	AAL1476-1547447160-airline-0028	1	3	0	1
DAL2256-1547619946-airline-0422	AAL1002-1547619942-airline-0011	1	2	1	0
DAL2259-1547619946-airline-0241	AAL1403-1547619942-airline-0246	0	2	1	0
DAL2280-1547447163-airline-0581	AAL1476-1547447160-airline-0028	0	1	1	1
DAL2280-1547447163-airline-0581	AAL1476-1547447160-airline-0028	0	3	1	1
DAL2340-1547447163-airline-0484	AAL1486-1547447160-airline-0145	0	2	1	0
DAL2342-1547360817-airline-0004	AAL1486-1547360814-airline-0154	0	3	1	0
DAL2351-1547533576-airline-0433	AAL1251-1547533573-airline-0395	0	1	0	1

ac1	ac2	target	type	option	mix
DAL2351-1547533576-airline-0433	AAL1251-1547533573-airline-0395	1	2	0	1
DAL2351-1547533576-airline-0433	AAL1251-1547533573-airline-0395	1	3	0	1
DAL2351-1547533576-airline-0433	AAL1251-1547533573-airline-0395	1	3	0	1
DAL2423-1547360817-airline-0090	AAL1161-1547360814-airline-0366	1	1	0	1
DAL2423-1547360817-airline-0090	AAL1161-1547360814-airline-0366	1	1	1	1
DAL2423-1547360817-airline-0090	AAL1161-1547360814-airline-0366	1	2	1	1
DAL2423-1547360817-airline-0090	AAL1161-1547360814-airline-0366	1	3	0	1
DAL2423-1547533576-airline-0381	AAL1239-1547533573-airline-0241	1	1	1	0
DAL2496-1547274359-airline-0427	AAL1246-1547274356-airline-0384	0	1	0	1
DAL2496-1547274359-airline-0427	AAL1246-1547274356-airline-0384	0	1	1	1
DAL2496-1547274359-airline-0427	AAL1246-1547274356-airline-0384	0	2	1	1
DAL2496-1547533576-airline-0359	AAL1251-1547533573-airline-0395	0	1	1	0
DAL2590-1547274359-airline-0179	AAL1486-1547274356-airline-0544	0	1	0	0
DAL2590-1547360817-airline-0443	AAL1486-1547360814-airline-0154	0	2	1	1
DAL2590-1547360817-airline-0443	AAL1486-1547360814-airline-0154	0	3	1	1
DAL2590-1547447163-airline-0255	AAL1486-1547447160-airline-0068	0	2	1	1
DAL2590-1547447163-airline-0255	AAL1486-1547447160-airline-0068	0	3	1	1
DAL2740-1547360817-airline-0375	AAL1002-1547360814-airline-0430	0	1	0	1
DAL2740-1547360817-airline-0375	AAL1002-1547360814-airline-0430	0	2	1	1

ac1	ac2	target	type	option	mix
DAL2740-1547360817-airline-0375	AAL1002-1547360814-airline-0430	1	2	0	1
DAL2740-1547360817-airline-0375	AAL1002-1547360814-airline-0430	1	3	0	1
DAL2918-1547447163-airline-0481	AAL1476-1547447160-airline-0028	0	1	1	1
DAL2918-1547447163-airline-0481	AAL1476-1547447160-airline-0028	0	2	1	1
DAL2918-1547447163-airline-0481	AAL1476-1547447160-airline-0028	0	3	1	1
DAL2918-1547447163-airline-0481	AAL1476-1547447160-airline-0028	1	3	1	1
DAL2935-1547533576-airline-0574	AAL1486-1547533573-airline-0364	0	1	0	1
DAL2935-1547533576-airline-0574	AAL1486-1547533573-airline-0364	1	3	0	1
DAL2935-1547533576-airline-0574	AAL1486-1547533573-airline-0364	1	3	0	1
DAL468-1547360817-airline-0274	AAL1246-1547360821-airline-0168	0	3	0	0
DAL712-1547274359-airline-0111	AAL1787-1547274356-airline-0532	1	2	0	0
DAL713-1547447163-airline-0054	AAL1002-1547447160-airline-0048	1	3	0	0
DAL713-1547619946-airline-0139	AAL1002-1547619942-airline-0011	1	2	1	1
DAL713-1547619946-airline-0139	AAL1002-1547619942-airline-0011	1	3	1	1
DAL85-1547360817-airline-0376	AAL1486-1547360814-airline-0154	0	1	1	0
DAL874-1547360818-airline-0050	AAL1486-1547360814-airline-0154	0	2	1	0
DAL950-1547360818-airline-0173	AAL1239-1547360814-airline-0248	1	3	0	0
DPJ48-1547584317-dlad-6214555	AAL1787-1547360814-airline-0367	1	1	0	1
DPJ48-1547584317-dlad-6214555	AAL1787-1547360814-airline-0367	1	1	0	1

ac1	ac2	target	type	option	mix
DPJ48-1547584317-dlad-6214555	AAL1787-1547360814-airline-0367	1	2	1	1
DPJ48-1547584317-dlad-6214555	AAL1787-1547360814-airline-0367	1	3	1	1
DPJ48-1547584317-dlad-6214555	AAL1787-1547360814-airline-0367	1	3	1	1
EDV5025-1547360827-airline-0041	AAL1486-1547360814-airline-0154	0	1	1	1
EDV5025-1547360827-airline-0041	AAL1486-1547360814-airline-0154	0	2	1	1
EDV5025-1547360827-airline-0041	AAL1486-1547360814-airline-0154	0	3	1	1
EJA319-1547603305-9-0-159	AAL1486-1547447160-airline-0145	1	2	1	0
EJA319-1547603305-9-0-159	AAL1492-1547447160-airline-0102	1	2	0	1
EJA319-1547603305-9-0-159	AAL1492-1547447160-airline-0102	1	3	0	1
EJA387-1547594744-8-1-220	AAL1246-1547360821-airline-0168	1	3	1	0
EJA387-1547755889-9-0-220	AAL1164-1547533573-airline-0091	0	1	1	1
EJA387-1547755889-9-0-220	AAL1164-1547533573-airline-0091	0	1	1	1
EJA387-1547755889-9-0-220	AAL1164-1547533573-airline-0091	0	2	1	1
ENY3407-1547533573-airline-0375	AAL1239-1547533573-airline-0241	1	1	0	1
ENY3407-1547533573-airline-0375	AAL1239-1547533573-airline-0241	1	1	0	1
ENY3407-1547533573-airline-0375	AAL1239-1547533573-airline-0241	1	2	0	1
ENY3407-1547533573-airline-0375	AAL1239-1547533573-airline-0241	1	3	0	1
ENY3477-1547447160-airline-0526	AAL1002-1547447160-airline-0048	1	1	0	1
ENY3477-1547447160-airline-0526	AAL1002-1547447160-airline-0048	1	2	1	1

ac1	ac2	target	type	option	mix
ENY3484-1547360814-airline-0583	AAL1239-1547360814-airline-0007	0	2	1	1
ENY3484-1547360814-airline-0583	AAL1239-1547360814-airline-0007	0	3	1	1
ENY4220-1547447160-airline-0199	AAL1239-1547447160-airline-0448	1	1	0	1
ENY4220-1547447160-airline-0199	AAL1239-1547447160-airline-0448	1	2	1	1
ENY4220-1547447160-airline-0199	AAL1239-1547447160-airline-0448	1	3	1	1
FDX1-1547504299-23-0-129	AAL166-1547360814-airline-0284	1	3	0	0
FDX3022-1547572710-3-0-137	AAL1161-1547447160-airline-0112	0	2	1	0
FDX34-1547549345-9-0-231	AAL1500-1547447160-airline-0076	0	3	1	0
FDX3736-1547504307-11-0-217	AAL1486-1547360814-airline-0154	1	3	0	0
FDX3736-1547590705-9-0-217	AAL1492-1547447160-airline-0102	0	1	1	1
FDX3736-1547590705-9-0-217	AAL1492-1547447160-airline-0102	0	2	1	1
FDX671-1547565530-9-0-148	AAL1002-1547447160-airline-0048	1	1	0	0
FDX764-1547677103-19-0-223	AAL1829-1547533573-airline-0217	0	2	1	1
FDX764-1547677103-19-0-223	AAL1829-1547533573-airline-0217	0	2	0	1
FDX764-1547677103-19-0-223	AAL1829-1547533573-airline-0217	1	2	0	1
FDX913-1547677138-1-0-89	AAL1486-1547533573-airline-0364	1	1	0	0
FDX981-1547594318-13-0-150	AAL1164-1547447160-airline-0335	0	3	1	0
FFT2195-1547360819-airline-0089	AAL1388-1547360814-airline-0474	1	1	0	0
FFT2542-1547360819-airline-0296	AAL1486-1547360814-airline-0154	1	2	0	0

ac1	ac2	target	type	option	mix
FFT2542-1547533577-airline-0106	AAL1829-1547533573-airline-0217	0	1	1	0
GGN7332-1547360825-airline-0059	AAL1-1547360814-airline-0035	1	2	1	1
GGN7332-1547360825-airline-0059	AAL1-1547360814-airline-0035	1	3	0	1
GGN7334-1547274356-airline-0097	AAL1486-1547274356-airline-0544	1	3	1	0
GGN7334-1547533583-airline-0008	AAL1486-1547533573-airline-0364	1	2	0	0
GJS4542-1547274367-airline-0376	AAL1388-1547274356-airline-0135	1	2	1	1
GJS4542-1547274367-airline-0376	AAL1388-1547274356-airline-0135	1	3	1	1
JBU1224-1547274358-airline-0085	AAL1246-1547274356-airline-0384	0	2	0	0
JBU1224-1547360816-airline-0368	AAL1246-1547360821-airline-0168	1	2	0	0
JBU134-1547533574-airline-0063	AAL1251-1547533573-airline-0395	0	1	1	0
JBU1785-1547533577-airline-0257	AAL1388-1547533573-airline-0085	1	2	1	0
JBU323-1547619945-airline-0076	AAL1002-1547619942-airline-0011	0	2	0	0
JBU324-1547447162-airline-0038	AAL1476-1547447160-airline-0028	0	2	1	1
JBU324-1547447162-airline-0038	AAL1476-1547447160-airline-0028	0	3	1	1
JBU397-1547619945-airline-0397	AAL1403-1547619942-airline-0246	0	2	1	1
JBU397-1547619945-airline-0397	AAL1403-1547619942-airline-0246	0	3	1	1
JBU397-1547619945-airline-0397	AAL1403-1547619942-airline-0246	0	3	1	1
JBU405-1547360816-airline-0346	AAL1486-1547360814-airline-0154	0	1	1	1
JBU405-1547360816-airline-0346	AAL1486-1547360814-airline-0154	0	1	1	1

ac1	ac2	target	type	option	mix
JBU415-1547360816-airline-0238	AAL1-1547360814-airline-0035	0	1	1	1
JBU415-1547360816-airline-0238	AAL1-1547360814-airline-0035	0	2	0	1
JBU415-1547360816-airline-0238	AAL1-1547360814-airline-0035	0	3	0	1
JBU415-1547447162-airline-0069	AAL1476-1547447160-airline-0028	1	2	0	0
JBU656-1547360816-airline-0189	AAL166-1547360814-airline-0284	1	1	1	0
JBU71-1547360816-airline-0375	AAL1388-1547360814-airline-0474	1	1	1	0
JBU871-1547533574-airline-0349	AAL1002-1547533573-airline-0042	1	1	0	1
JBU871-1547533574-airline-0349	AAL1002-1547533573-airline-0042	1	2	0	1
JBU871-1547533574-airline-0349	AAL1002-1547533573-airline-0042	1	3	1	1
JIA5079-1547360814-airline-0238	AAL1486-1547360814-airline-0154	0	3	1	0
JIA5079-1547447160-airline-0292	AAL1486-1547447160-airline-0145	1	3	0	0
JIA5079-1547533573-airline-0579	AAL1187-1547533573-airline-0504	0	2	1	1
JIA5079-1547533573-airline-0579	AAL1187-1547533573-airline-0504	0	3	1	1
JIA5079-1547533573-airline-0579	AAL1486-1547533573-airline-0364	1	2	1	1
JIA5079-1547533573-airline-0579	AAL1486-1547533573-airline-0364	1	3	1	1
JIA5324-1547360814-airline-0682	AAL1081-1547360814-airline-0288	0	1	1	1
JIA5324-1547360814-airline-0682	AAL1081-1547360814-airline-0288	0	2	0	1
JIA5324-1547360814-airline-0682	AAL1081-1547360814-airline-0288	0	3	0	1
JIA5479-1547447160-airline-0672	AAL1002-1547447160-airline-0048	0	3	1	0

ac1	ac2	target	type	option	mix
JIA5480-1547447160-airline-0460	AAL1002-1547447160-airline-0048	1	1	0	1
JIA5480-1547447160-airline-0460	AAL1002-1547447160-airline-0048	1	2	1	1
JIA5480-1547447160-airline-0460	AAL1002-1547447160-airline-0048	1	3	0	1
JIA9912-1547757177-31-0-87	AAL1164-1547533573-airline-0091	1	2	1	1
JIA9912-1547757177-31-0-87	AAL1164-1547533573-airline-0091	0	2	0	1
JNY7-1547476558-dlad-6211898	AAL1486-1547274356-airline-0544	0	3	0	0
KAL94-1547360820-airline-0396	AAL1161-1547360814-airline-0366	1	1	0	1
KAL94-1547360820-airline-0396	AAL1161-1547360814-airline-0366	1	2	1	1
KAL94-1547360820-airline-0396	AAL1161-1547360814-airline-0366	1	3	0	1
KLM662-1547533579-airline-0018	AAL1187-1547533573-airline-0504	1	3	0	0
LOF4602-1547533580-airline-0330	AAL1486-1547533573-airline-0364	1	2	1	1
LOF4602-1547533580-airline-0330	AAL1486-1547533573-airline-0364	1	3	1	1
LXJ536-1547660398-2-0-94	AAL1239-1547447160-airline-0448	0	2	1	1
LXJ536-1547660398-2-0-94	AAL1239-1547447160-airline-0448	0	3	1	1
MNU8012-1547582651-1-0-167	AAL1486-1547360814-airline-0154	1	3	0	1
MNU8012-1547582651-1-0-167	AAL1486-1547360814-airline-0154	1	3	0	1
N175MX-1547427582-0-0-230	AAL1486-1547274356-airline-0544	0	2	0	1
N175MX-1547427582-0-0-230	AAL1486-1547274356-airline-0544	0	3	1	1
N21HJ-1547498679-5-1-149	AAL1787-1547274356-airline-0532	1	3	0	0

ac1	ac2	target	type	option	mix
N417JD-1547668748-16-0-154	AAL1002-1547533573-airline-0042	1	2	1	0
N562BC-1547816765-9-0-132	AAL1002-1547619942-airline-0011	0	2	1	0
N757CC-1547751631-dlad-6218846	AAL1829-1547533573-airline-0217	1	1	1	1
N757CC-1547751631-dlad-6218846	AAL1829-1547533573-airline-0217	1	2	1	1
N757CC-1547751631-dlad-6218846	AAL1829-1547533573-airline-0217	1	3	0	1
N770CC-1547668820-4-1-80	AAL1486-1547447160-airline-0068	1	1	0	1
N770CC-1547668820-4-1-80	AAL1486-1547447160-airline-0068	1	2	1	1
N770CC-1547668820-4-1-80	AAL1486-1547447160-airline-0068	1	3	1	1
N770CC-1547668820-4-1-80	AAL1486-1547447160-airline-0068	1	3	1	1
N81ER-1547506721-1-2-4	AAL1239-1547360814-airline-0007	1	3	0	0
N971MT-1547658415-0-0-140	AAL1486-1547447160-airline-0145	1	3	0	0
NKS1419-1547360823-airline-0324	AAL1164-1547360814-airline-0373	1	2	1	1
NKS1419-1547360823-airline-0324	AAL1164-1547360814-airline-0373	1	2	0	1
NKS1419-1547360823-airline-0324	AAL1164-1547360814-airline-0373	1	3	0	1
NKS282-1547274364-airline-0037	AAL1486-1547274356-airline-0544	0	1	1	1
NKS282-1547274364-airline-0037	AAL1486-1547274356-airline-0544	0	2	0	1
NKS282-1547274364-airline-0037	AAL1486-1547274356-airline-0544	0	3	1	1
NKS282-1547274364-airline-0037	AAL1787-1547274356-airline-0532	1	2	0	1
NKS282-1547274364-airline-0037	AAL1787-1547274356-airline-0532	0	2	0	1

ac1	ac2	target	type	option	mix
NKS614-1547533581-airline-0390	AAL1164-1547533573-airline-0091	1	2	0	1
NKS614-1547533581-airline-0390	AAL1164-1547533573-airline-0091	0	2	1	1
NKS614-1547533581-airline-0390	AAL1187-1547533573-airline-0504	0	2	0	0
NKS631-1547360823-airline-0063	AAL1164-1547360814-airline-0373	1	2	0	0
NKS631-1547360823-airline-0063	AAL1486-1547360814-airline-0154	0	1	1	1
NKS631-1547360823-airline-0063	AAL1486-1547360814-airline-0154	0	2	1	1
NKS631-1547360823-airline-0063	AAL1486-1547360814-airline-0154	0	3	1	1
NKS636-1547360823-airline-0275	AAL1486-1547360814-airline-0154	0	3	1	0
NKS641-1547447168-airline-0281	AAL1486-1547447160-airline-0068	1	1	0	1
NKS641-1547447168-airline-0281	AAL1486-1547447160-airline-0068	0	1	1	1
NKS641-1547447168-airline-0281	AAL1486-1547447160-airline-0068	0	2	0	1
NKS641-1547447168-airline-0281	AAL1486-1547447160-airline-0068	0	3	0	1
NKS641-1547447168-airline-0281	AAL1486-1547447160-airline-0068	0	3	0	1
NKS678-1547360823-airline-0339	AAL1164-1547360814-airline-0373	1	2	0	1
NKS678-1547360823-airline-0339	AAL1164-1547360814-airline-0373	1	3	1	1
NKS678-1547533581-airline-0275	AAL1187-1547533573-airline-0504	0	1	1	0
NKS761-1547619951-airline-0291	AAL1002-1547619942-airline-0011	1	3	0	0
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	1	2	1	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	2	0	1

ac1	ac2	target	type	option	mix
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	2	0	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	1	3	1	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	3	1	1
NKS847-1547447168-airline-0409	AAL1239-1547447160-airline-0465	0	1	1	1
NKS847-1547447168-airline-0409	AAL1239-1547447160-airline-0465	0	2	1	1
NKS847-1547447168-airline-0409	AAL1239-1547447160-airline-0465	0	2	0	1
NKS847-1547447168-airline-0409	AAL1239-1547447160-airline-0465	0	3	1	1
NKS993-1547619951-airline-0326	AAL1002-1547619942-airline-0011	1	3	0	0
PDT4814-1547360814-airline-0249	AAL1239-1547360814-airline-0007	1	1	0	1
PDT4814-1547360814-airline-0249	AAL1239-1547360814-airline-0007	1	2	1	1
PDT4814-1547360814-airline-0249	AAL1239-1547360814-airline-0007	1	3	1	1
PDT4814-1547533573-airline-0595	AAL1239-1547533573-airline-0241	0	1	1	1
PDT4814-1547533573-airline-0595	AAL1239-1547533573-airline-0241	0	2	1	1
PDT4814-1547533573-airline-0595	AAL1239-1547533573-airline-0241	0	3	1	1
QFA12-1547447169-airline-0008	AAL1164-1547447160-airline-0335	0	1	1	1
QFA12-1547447169-airline-0008	AAL1164-1547447160-airline-0335	0	2	1	1
QFA12-1547447169-airline-0008	AAL1164-1547447160-airline-0335	1	2	0	1
QFA12-1547447169-airline-0008	AAL1164-1547447160-airline-0335	0	3	1	1
QFA12-1547447169-airline-0008	AAL1164-1547447160-airline-0335	1	3	0	1

ac1	ac2	target	type	option	mix
ROU1659-1547274356-airline-0109	AAL1164-1547274356-airline-0307	0	1	1	0
ROU1665-1547274356-airline-0213	AAL1164-1547274356-airline-0307	0	2	1	1
ROU1665-1547274356-airline-0213	AAL1164-1547274356-airline-0307	0	3	1	1
ROU1665-1547274356-airline-0213	AAL1246-1547274356-airline-0384	1	1	0	1
ROU1665-1547274356-airline-0213	AAL1246-1547274356-airline-0384	1	2	1	1
ROU1665-1547274356-airline-0213	AAL1246-1547274356-airline-0384	1	3	1	1
ROU1665-1547274356-airline-0213	AAL1246-1547274356-airline-0384	1	3	0	1
ROU1665-1547533573-airline-0096	AAL1640-1547533573-airline-0272	0	1	1	0
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	0	1	1	1
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	0	1	0	1
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	0	2	1	1
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	0	3	0	1
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	0	3	0	1
ROU1749-1547274356-airline-0145	AAL1246-1547274356-airline-0384	1	3	0	1
RPA3416-1547274367-airline-0381	AAL1164-1547274356-airline-0307	1	2	1	1
RPA3416-1547274367-airline-0381	AAL1164-1547274356-airline-0307	1	3	1	1
RPA3417-1547447168-airline-0226	AAL1002-1547447160-airline-0048	0	1	1	0
RPA3489-1547274367-airline-0127	AAL1246-1547274356-airline-0384	1	3	0	0
RPA3570-1547360824-airline-0018	AAL1-1547360814-airline-0035	0	2	1	1

ac1	ac2	target	type	option	mix
RPA3570-1547360824-airline-0018	AAL1-1547360814-airline-0035	0	3	0	1
RPA4380-1547447160-airline-0353	AAL1486-1547447160-airline-0068	0	1	1	1
RPA4380-1547447160-airline-0353	AAL1486-1547447160-airline-0068	0	1	1	1
RPA4380-1547447160-airline-0353	AAL1486-1547447160-airline-0068	0	2	1	1
RPA4380-1547447160-airline-0353	AAL1486-1547447160-airline-0068	0	3	1	1
RPA4380-1547533573-airline-0705	AAL1486-1547533573-airline-0364	1	2	1	1
RPA4380-1547533573-airline-0705	AAL1486-1547533573-airline-0364	1	3	1	1
RPA4381-1547533573-airline-0519	AAL1002-1547533573-airline-0042	1	2	1	0
RPA4383-1547447160-airline-0319	AAL1002-1547447160-airline-0048	1	3	0	0
RPA4383-1547533573-airline-0331	AAL1002-1547533573-airline-0042	0	2	1	1
RPA4383-1547533573-airline-0331	AAL1002-1547533573-airline-0042	1	3	1	1
RPA4621-1547447160-airline-0205	AAL1002-1547447160-airline-0048	1	2	1	1
RPA4621-1547447160-airline-0205	AAL1002-1547447160-airline-0048	1	3	1	1
RPA4712-1547274356-airline-0114	AAL1164-1547274356-airline-0307	1	2	0	1
RPA4712-1547274356-airline-0114	AAL1164-1547274356-airline-0307	1	3	0	1
RPA5911-1547360817-airline-0122	AAL1239-1547360814-airline-0007	0	1	0	1
RPA5911-1547360817-airline-0122	AAL1239-1547360814-airline-0007	0	3	1	1
RPA5911-1547447173-airline-0154	AAL1239-1547447160-airline-0448	1	1	0	1
RPA5911-1547447173-airline-0154	AAL1239-1547447160-airline-0448	1	3	0	1

ac1	ac2	target	type	option	mix
RPA5915-1547360817-airline-0260	AAL1-1547360814-airline-0035	0	1	0	1
RPA5915-1547360817-airline-0260	AAL1-1547360814-airline-0035	1	1	0	1
RPA5915-1547360817-airline-0260	AAL1-1547360814-airline-0035	0	2	1	1
RPA5915-1547360817-airline-0260	AAL1-1547360814-airline-0035	1	3	0	1
RPA6007-1547619946-airline-0259	AAL1002-1547619942-airline-0011	0	2	1	0
SKW3659-1547619955-airline-0000	AAL1002-1547619942-airline-0011	0	3	0	0
SKW3749-1547533586-airline-0037	AAL1829-1547533573-airline-0217	1	1	1	1
SKW3749-1547533586-airline-0037	AAL1829-1547533573-airline-0217	0	2	1	1
SKW3749-1547533586-airline-0037	AAL1829-1547533573-airline-0217	0	3	1	1
SKW3752-1547533576-airline-0555	AAL1251-1547533573-airline-0395	1	2	1	1
SKW3752-1547533576-airline-0555	AAL1251-1547533573-airline-0395	1	3	1	1
SKW3820-1547360826-airline-0029	AAL1002-1547360814-airline-0430	0	1	1	1
SKW3820-1547360826-airline-0029	AAL1002-1547360814-airline-0430	0	2	0	1
SKW3820-1547360826-airline-0029	AAL1002-1547360814-airline-0430	0	3	0	1
SKW3820-1547360826-airline-0029	AAL1002-1547360814-airline-0430	0	3	0	1
SKW3820-1547360826-airline-0029	AAL1002-1547360814-airline-0430	0	3	0	1
SKW3822-1547619955-airline-0037	AAL1002-1547619942-airline-0011	1	2	0	0
SKW3825-1547360826-airline-0143	AAL1161-1547360814-airline-0366	1	1	0	1
SKW3825-1547360826-airline-0143	AAL1161-1547360814-airline-0366	1	1	1	1

ac1	ac2	target	type	option	mix
SKW3825-1547360826-airline-0143	AAL1161-1547360814-airline-0366	1	3	1	1
SKW3825-1547360826-airline-0143	AAL1161-1547360814-airline-0366	1	3	0	1
SKW3825-1547360826-airline-0143	AAL1239-1547360814-airline-0007	0	1	0	1
SKW3825-1547360826-airline-0143	AAL1239-1547360814-airline-0007	0	3	0	1
SKW3900-1547360826-airline-0126	AAL1081-1547360814-airline-0288	0	3	1	0
SKW4318-1547447163-airline-0087	AAL1239-1547447160-airline-0448	1	2	1	0
SKW4318-1547533576-airline-0310	AAL1239-1547533573-airline-0241	1	2	1	0
SKW4321-1547360817-airline-0144	AAL1002-1547360814-airline-0430	1	1	0	0
SKW5208-1547533584-airline-0463	AAL1002-1547533573-airline-0042	1	2	1	1
SKW5208-1547533584-airline-0463	AAL1002-1547533573-airline-0042	1	3	1	1
SWA104-1547360826-airline-0004	AAL1164-1547360814-airline-0373	0	1	1	1
SWA104-1547360826-airline-0004	AAL1164-1547360814-airline-0373	0	2	1	1
SWA104-1547360826-airline-0004	AAL1164-1547360814-airline-0373	0	3	1	1
SWA1307-1547533585-airline-0395	AAL1164-1547533573-airline-0091	0	1	1	0
SWA1849-1547360826-airline-0685	AAL1164-1547360814-airline-0373	0	1	1	0
SWA337-1547447172-airline-0222	AAL1476-1547447160-airline-0028	0	3	0	0
SWA744-1547447172-airline-0453	AAL1486-1547447160-airline-0145	0	1	1	1
SWA744-1547447172-airline-0453	AAL1486-1547447160-airline-0145	0	2	0	1
SWA744-1547447172-airline-0453	AAL1486-1547447160-airline-0145	0	3	1	1

ac1	ac2	target	type	option	mix
SWA891-1547533585-airline-0112	AAL1251-1547533573-airline-0395	0	1	0	1
SWA891-1547533585-airline-0112	AAL1251-1547533573-airline-0395	1	2	0	1
SWA891-1547533585-airline-0112	AAL1251-1547533573-airline-0395	0	3	0	1
SWG253-1547274368-airline-0243	AAL166-1547274356-airline-0132	1	1	1	0
SWG313-1547572245-1-0-6	AAL166-1547360814-airline-0284	1	3	0	0
SWG721-1547533585-airline-0503	AAL1187-1547533573-airline-0504	1	2	0	1
SWG721-1547533585-airline-0503	AAL1187-1547533573-airline-0504	0	3	1	1
SWG721-1547533585-airline-0503	AAL1787-1547533573-airline-0048	0	1	0	1
SWG721-1547533585-airline-0503	AAL1787-1547533573-airline-0048	1	3	0	1
SWG783-1547496040-6-0-143	AAL1388-1547274356-airline-0135	1	1	0	0
THY34-1547533583-airline-0211	AAL1640-1547533573-airline-0272	1	3	1	0
UAL1056-1547447171-airline-0081	AAL1002-1547447160-airline-0048	1	3	0	0
UAL1284-1547520016-fa-0000	AAL1486-1547533573-airline-0364	0	3	1	0
UAL1535-1547360825-airline-0097	AAL1486-1547360814-airline-0154	1	2	0	0
UAL2098-1547558906-fa-0002	AAL1002-1547619942-airline-0011	1	1	0	0
UAL2337-1547417412-fa-0011	AAL1476-1547447160-airline-0028	0	1	1	1
UAL2337-1547417412-fa-0011	AAL1476-1547447160-airline-0028	0	2	1	1
UAL2337-1547417412-fa-0011	AAL1476-1547447160-airline-0028	0	3	0	1
UAL2337-1547417412-fa-0011	AAL1476-1547447160-airline-0028	0	3	0	1

ac1	ac2	target	type	option	mix
UAL2418-1547360825-airline-0031	AAL1161-1547360814-airline-0366	0	3	0	0
UAL242-1547245110-fa-0004	AAL1388-1547274356-airline-0135	0	1	1	1
UAL242-1547245110-fa-0004	AAL1388-1547274356-airline-0135	0	3	1	1
UAL2429-1547337922-fa-0003	AAL1486-1547360814-airline-0154	1	3	0	0
UAL322-1547360825-airline-0144	AAL1-1547360814-airline-0035	1	1	1	0
UAL322-1547360825-airline-0144	AAL1002-1547360814-airline-0430	1	1	0	0
UAL322-1547447171-airline-0398	AAL1002-1547447160-airline-0048	1	2	1	0
UAL326-1547447171-airline-0129	AAL1486-1547447160-airline-0068	0	3	0	0
UAL473-1547273704-fa-0003	AAL1486-1547274356-airline-0544	1	1	0	1
UAL473-1547273704-fa-0003	AAL1486-1547274356-airline-0544	1	2	1	1
UAL473-1547273704-fa-0003	AAL1486-1547274356-airline-0544	1	3	1	1
UAL473-1547360104-fa-0000	AAL1486-1547360814-airline-0154	1	1	0	1
UAL473-1547360104-fa-0000	AAL1486-1547360814-airline-0154	1	1	0	1
UAL473-1547360104-fa-0000	AAL1486-1547360814-airline-0154	1	2	1	1
UAL473-1547360104-fa-0000	AAL1486-1547360814-airline-0154	0	2	1	1
UAL473-1547360104-fa-0000	AAL1486-1547360814-airline-0154	1	3	1	1
UAL493-1547533584-airline-0155	AAL1829-1547533573-airline-0217	1	2	1	0
UAL503-1547274367-airline-0324	AAL166-1547274356-airline-0132	1	1	0	1
UAL503-1547274367-airline-0324	AAL166-1547274356-airline-0132	1	3	1	1

ac1	ac2	target	type	option	mix
UAL642-1547444959-fa-0000	AAL1476-1547447160-airline-0028	0	1	1	0
UAL719-1547272323-fa-0005	AAL1486-1547274356-airline-0544	1	1	0	0
UAL788-1547274367-airline-0166	AAL1164-1547274356-airline-0307	1	3	0	0
UAL788-1547274367-airline-0166	AAL1246-1547274356-airline-0384	0	1	0	1
UAL788-1547274367-airline-0166	AAL1246-1547274356-airline-0384	1	2	0	1
UAL788-1547274367-airline-0166	AAL1246-1547274356-airline-0384	1	3	0	1
UAL789-1547533584-airline-0134	AAL1239-1547533573-airline-0241	0	3	0	0
UAL803-1547514250-fa-0000	AAL1388-1547533573-airline-0085	1	1	1	0
UCA4940-1547447171-airline-0383	AAL1002-1547447160-airline-0048	1	1	0	1
UCA4940-1547447171-airline-0383	AAL1002-1547447160-airline-0048	1	2	1	1
UCA4940-1547447171-airline-0383	AAL1002-1547447160-airline-0048	1	3	1	1
UPS1189-1547468243-2-0-219	AAL1164-1547274356-airline-0307	0	1	1	1
UPS1189-1547468243-2-0-219	AAL1164-1547274356-airline-0307	1	1	0	1
UPS2013-1547683955-3-1-48	AAL1002-1547533573-airline-0042	1	2	1	1
UPS2013-1547683955-3-1-48	AAL1002-1547533573-airline-0042	1	3	1	1
UPS2079-1547596959-5-0-108	AAL1002-1547447160-airline-0048	1	3	0	0
UPS218-1547686961-0-1-99	AAL1002-1547533573-airline-0042	0	1	1	1
UPS218-1547686961-0-1-99	AAL1002-1547533573-airline-0042	0	2	1	1
UPS2955-1547505459-2-1-65	AAL1-1547360814-airline-0035	0	1	1	1

ac1	ac2	target	type	option	mix
UPS2955-1547505459-2-1-65	AAL1-1547360814-airline-0035	0	3	0	1
UPS2956-1547529460-0-1-66	AAL1388-1547360814-airline-0474	1	3	0	0
UPS2956-1547702253-4-0-66	AAL1187-1547533573-airline-0504	1	1	1	0
UPS2956-1547702253-4-0-66	AAL1486-1547533573-airline-0364	1	3	0	0
WJA1246-1547360826-airline-0591	AAL1239-1547360814-airline-0248	0	1	1	1
WJA1246-1547360826-airline-0591	AAL1239-1547360814-airline-0248	0	2	1	1
WJA1246-1547360826-airline-0591	AAL1239-1547360814-airline-0248	0	3	1	1
WJA2766-1547360826-airline-0060	AAL1-1547360814-airline-0035	1	1	0	0
XOJ536-1547546478-5-1-133	AAL1-1547360814-airline-0035	1	1	0	1
XOJ536-1547546478-5-1-133	AAL1-1547360814-airline-0035	1	2	0	1

A.6.3 Predicted Aircraft Conflicts of ZTL

ac1	ac2	target	type	option	mix
AAL1495-1547619949-airline-0065	AAL1478-1547619942-airline-0299	1	1	0	0
AAL1809-1547447160-airline-0208	AAL1500-1547447160-airline-0076	0	2	0	0
AAL1809-1547447160-airline-0208	AAL1669-1547447160-airline-0508	0	1	1	0
AAL1816-1547274356-airline-0175	AAL1076-1547274356-airline-0108	1	1	0	1
AAL1816-1547274356-airline-0175	AAL1076-1547274356-airline-0108	0	2	0	1
AAL1816-1547274356-airline-0175	AAL1076-1547274356-airline-0108	0	3	1	1
AAL1865-1547360814-airline-0600	AAL1500-1547360814-airline-0316	1	1	1	1
AAL1865-1547360814-airline-0600	AAL1500-1547360814-airline-0316	1	2	1	1
AAL1865-1547360814-airline-0600	AAL1500-1547360814-airline-0316	0	2	0	1
AAL1865-1547360814-airline-0600	AAL1500-1547360814-airline-0316	0	3	1	1
AAL1929-1547360814-airline-0285	AAL1654-1547454346-airline-0009	0	3	1	0
AAL1955-1547360814-airline-0478	AAL147-1547360821-airline-0205	0	1	1	1
AAL1955-1547360814-airline-0478	AAL147-1547360821-airline-0205	0	2	0	1
AAL1955-1547360814-airline-0478	AAL147-1547360821-airline-0205	0	3	0	1
AAL2211-1547360814-airline-0462	AAL1476-1547360814-airline-0413	1	2	0	0
AAL2213-1547274356-airline-0059	AAL147-1547274355-airline-0025	1	1	0	0
AAL2213-1547533573-airline-0010	AAL147-1547533579-airline-0037	0	1	1	1
AAL2213-1547533573-airline-0010	AAL147-1547533579-airline-0037	0	1	1	1

ac1	ac2	target	type	option	mix
AAL2213-1547533573-airline-0010	AAL147-1547533579-airline-0037	0	2	1	1
AAL2213-1547533573-airline-0010	AAL147-1547533579-airline-0037	0	3	1	1
AAL2323-1547360821-airline-0020	AAL1654-1547367925-airline-0066	0	1	1	1
AAL2323-1547360821-airline-0020	AAL1654-1547367925-airline-0066	0	2	1	1
AAL2323-1547360821-airline-0020	AAL1654-1547367925-airline-0066	0	3	1	1
AAL233-1547360814-airline-0085	AAL1002-1547360814-airline-0446	1	1	0	0
AAL2521-1547360814-airline-0289	AAL1490-1547360814-airline-0509	0	3	0	0
AAL2544-1547360814-airline-0019	AAL1631-1547360814-airline-0222	0	1	1	1
AAL2544-1547360814-airline-0019	AAL1631-1547360814-airline-0222	0	2	1	1
AAL2544-1547360814-airline-0019	AAL1631-1547360814-airline-0222	1	3	1	1
AAL2602-1547533573-airline-0132	AAL1172-1547533573-airline-0084	0	1	1	1
AAL2602-1547533573-airline-0132	AAL1172-1547533573-airline-0084	0	3	1	1
AAL299-1547274356-airline-0011	AAL1076-1547274356-airline-0108	1	1	0	1
AAL299-1547274356-airline-0011	AAL1076-1547274356-airline-0108	1	2	0	1
AAL299-1547274356-airline-0011	AAL1076-1547274356-airline-0108	0	3	1	1
AAL299-1547274356-airline-0011	AAL1076-1547274356-airline-0108	1	3	0	1
AAL36-1547533573-airline-0371	AAL1159-1547533573-airline-0327	0	3	0	0
AAL485-1547447160-airline-0700	AAL1500-1547447160-airline-0076	0	1	1	1
AAL485-1547447160-airline-0700	AAL1500-1547447160-airline-0076	0	2	1	1

ac1	ac2	target	type	option	mix
AAL485-1547447160-airline-0700	AAL1500-1547447160-airline-0076	0	2	0	1
AAL485-1547447160-airline-0700	AAL1500-1547447160-airline-0076	0	3	1	1
AAL553-1547447160-airline-0211	AAL1164-1547447160-airline-0296	1	3	0	0
AAL558-1547447160-airline-0585	AAL1164-1547447160-airline-0296	0	2	1	0
AAL703-1547274356-airline-0045	AAL1164-1547274356-airline-0307	0	2	1	0
AAL855-1547274356-airline-0190	AAL1076-1547274356-airline-0108	0	2	1	1
AAL855-1547274356-airline-0190	AAL1076-1547274356-airline-0108	0	3	1	1
AAL863-1547447160-airline-0037	AAL1489-1547447160-airline-0227	1	1	0	0
AAL863-1547533573-airline-0209	AAL1164-1547533573-airline-0006	1	1	0	1
AAL863-1547533573-airline-0209	AAL1164-1547533573-airline-0006	1	3	1	1
AAL863-1547533573-airline-0209	AAL1476-1547533573-airline-0608	1	1	0	0
AAY2227-1547274360-airline-0018	AAL1164-1547274356-airline-0307	1	3	0	0
AAY858-1547533578-airline-0074	AAL1164-1547533573-airline-0091	1	2	0	1
AAY858-1547533578-airline-0074	AAL1164-1547533573-airline-0091	0	2	0	1
AAY859-1547619947-airline-0566	AAL1478-1547619942-airline-0299	1	3	1	0
AAY880-1547619947-airline-0504	AAL1476-1547619942-airline-0544	1	2	1	1
AAY880-1547619947-airline-0504	AAL1476-1547619942-airline-0544	0	2	0	1
ABX902-1547518555-1-0-212	AAL1164-1547274356-airline-0307	0	3	0	0
AIJ2811-1547533572-airline-0180	AAL147-1547533579-airline-0037	0	2	1	0

ac1	ac2	target	type	option	mix
AIJ2840-1547533572-airline-0187	AAL1172-1547533573-airline-0084	1	1	0	1
AIJ2840-1547533572-airline-0187	AAL1172-1547533573-airline-0084	1	2	0	1
AIJ2841-1547619942-airline-0117	AAL1478-1547619942-airline-0299	1	1	1	1
AIJ2841-1547619942-airline-0117	AAL1478-1547619942-airline-0299	1	3	0	1
AMX404-1547274356-airline-0074	AAL1155-1547274356-airline-0430	1	1	0	0
AMX636-1547533574-airline-0015	AAL1172-1547533573-airline-0084	1	3	0	0
ASA9575-1547562151-adhoc-0	AAL1164-1547360814-airline-0358	1	2	0	0
ASH6199-1547619951-airline-0154	AAL145-1547619949-airline-0330	1	3	1	0
ASH6208-1547274367-airline-0204	AAL1076-1547274356-airline-0108	0	2	1	1
ASH6208-1547274367-airline-0204	AAL1076-1547274356-airline-0108	1	3	1	1
ASH6208-1547360823-airline-0101	AAL1172-1547360814-airline-0425	0	3	1	0
ASH6208-1547533584-airline-0418	AAL1076-1547533573-airline-0151	1	2	0	0
ASH6296-1547447171-airline-0035	AAL1159-1547447160-airline-0130	1	1	1	0
ASH6300-1547619951-airline-0043	AAL1478-1547619942-airline-0299	0	1	0	1
ASH6300-1547619951-airline-0043	AAL1478-1547619942-airline-0299	1	1	0	1
ASH6300-1547619951-airline-0043	AAL1478-1547619942-airline-0299	0	2	0	1
ASH6300-1547619951-airline-0043	AAL1478-1547619942-airline-0299	1	3	0	1
ASH6312-1547533584-airline-0125	AAL1240-1547533573-airline-0111	0	1	1	1
ASH6312-1547533584-airline-0125	AAL1240-1547533573-airline-0111	0	2	0	1

ac1	ac2	target	type	option	mix
ASH6363-1547274358-airline-0168	AAL1164-1547274356-airline-0307	1	2	1	1
ASH6363-1547274358-airline-0168	AAL1164-1547274356-airline-0307	1	3	1	1
COL901-1547408528-dlad-6210646	AAL1159-1547274356-airline-0484	1	1	0	1
COL901-1547408528-dlad-6210646	AAL1159-1547274356-airline-0484	1	3	1	1
COL976-1547586246-dlad-6214608	AAL1159-1547447160-airline-0130	1	2	0	0
CPA2091-1547360900-airline-0087	AAL1471-1547360821-airline-0418	0	1	0	0
DAL1055-1547360817-airline-0404	AAL1638-1547360814-airline-0356	0	2	1	0
DAL1219-1547360817-airline-0457	AAL1164-1547360814-airline-0358	1	1	0	0
DAL1219-1547447163-airline-0154	AAL1164-1547447160-airline-0296	1	1	0	0
DAL1224-1547360817-airline-0113	AAL1159-1547360814-airline-0338	0	1	1	1
DAL1224-1547360817-airline-0113	AAL1159-1547360814-airline-0338	0	3	0	1
DAL1352-1547360817-airline-0354	AAL1471-1547360821-airline-0418	1	3	0	0
DAL1369-1547274359-airline-0552	AAL1155-1547274356-airline-0430	1	2	1	0
DAL1528-1547533576-airline-0564	AAL1159-1547533573-airline-0327	1	2	0	0
DAL1530-1547360817-airline-0452	AAL1476-1547360814-airline-0413	1	2	1	1
DAL1530-1547360817-airline-0452	AAL1476-1547360814-airline-0413	1	3	1	1
DAL1530-1547447163-airline-0440	AAL1164-1547447160-airline-0296	1	1	0	1
DAL1530-1547447163-airline-0440	AAL1164-1547447160-airline-0296	1	2	1	1
DAL1530-1547447163-airline-0440	AAL1164-1547447160-airline-0296	1	2	0	1

ac1	ac2	target	type	option	mix
DAL1530-1547447163-airline-0440	AAL1164-1547447160-airline-0296	1	3	1	1
DAL1533-1547619946-airline-0616	AAL1166-1547619942-airline-0541	1	1	0	0
DAL1534-1547360817-airline-0192	AAL1476-1547360814-airline-0413	1	3	1	0
DAL1534-1547447163-airline-0075	AAL1164-1547447160-airline-0296	1	2	1	0
DAL1534-1547533576-airline-0441	AAL1164-1547533573-airline-0006	1	3	1	0
DAL1853-1547619946-airline-0653	AAL1166-1547619942-airline-0541	0	1	1	1
DAL1853-1547619946-airline-0653	AAL1166-1547619942-airline-0541	1	2	1	1
DAL1853-1547619946-airline-0653	AAL1166-1547619942-airline-0541	0	2	1	1
DAL1853-1547619946-airline-0653	AAL1166-1547619942-airline-0541	0	3	0	1
DAL1858-1547533576-airline-0027	AAL1164-1547533573-airline-0006	1	1	1	1
DAL1858-1547533576-airline-0027	AAL1164-1547533573-airline-0006	1	2	0	1
DAL1865-1547533576-airline-0267	AAL1164-1547533573-airline-0091	0	2	1	1
DAL1865-1547533576-airline-0267	AAL1164-1547533573-airline-0091	0	3	1	1
DAL2271-1547533576-airline-0311	AAL1240-1547533573-airline-0111	0	1	1	0
DAL2275-1547447163-airline-0611	AAL1166-1547447160-airline-0300	0	2	1	1
DAL2275-1547447163-airline-0611	AAL1166-1547447160-airline-0300	0	3	1	1
DAL2282-1547447163-airline-0031	AAL1164-1547447160-airline-0296	1	2	1	1
DAL2282-1547447163-airline-0031	AAL1164-1547447160-airline-0296	0	3	1	1
DAL2342-1547360817-airline-0004	AAL1159-1547360814-airline-0338	0	1	1	1

ac1	ac2	target	type	option	mix
DAL2342-1547360817-airline-0004	AAL1159-1547360814-airline-0338	0	3	1	1
DAL2342-1547360817-airline-0004	AAL1172-1547360814-airline-0425	0	3	0	0
DAL2589-1547360817-airline-0249	AAL1002-1547360814-airline-0446	1	1	0	0
DAL2591-1547360817-airline-0297	AAL1164-1547360814-airline-0358	1	1	0	1
DAL2591-1547360817-airline-0297	AAL1164-1547360814-airline-0358	1	2	1	1
DAL2591-1547360817-airline-0297	AAL1164-1547360814-airline-0358	1	3	0	1
DAL2591-1547360817-airline-0297	AAL1164-1547360814-airline-0358	1	3	1	1
DAL2593-1547619946-airline-0491	AAL1166-1547619942-airline-0541	1	2	0	0
DAL2609-1547533576-airline-0510	AAL1164-1547533573-airline-0006	1	3	0	0
DAL2661-1547360817-airline-0387	AAL1172-1547360814-airline-0425	0	2	1	1
DAL2661-1547360817-airline-0387	AAL1172-1547360814-airline-0425	1	3	1	1
DAL2887-1547360817-airline-0004	AAL1476-1547360814-airline-0413	1	2	1	1
DAL2887-1547360817-airline-0004	AAL1476-1547360814-airline-0413	1	3	0	1
DAL2887-1547447163-airline-0356	AAL1164-1547447160-airline-0296	1	2	1	0
DAL2887-1547533576-airline-0175	AAL1476-1547533573-airline-0608	1	2	1	0
DAL2902-1547360817-airline-0431	AAL1164-1547360814-airline-0358	0	1	1	1
DAL2902-1547360817-airline-0431	AAL1164-1547360814-airline-0358	0	2	1	1
DAL2902-1547360817-airline-0431	AAL1164-1547360814-airline-0358	0	3	1	1
DAL2902-1547360817-airline-0431	AAL1476-1547360814-airline-0413	1	2	0	0

ac1	ac2	target	type	option	mix
DAL2902-1547447163-airline-0258	AAL1164-1547447160-airline-0296	0	2	0	0
DAL2905-1547533576-airline-0586	AAL1076-1547533573-airline-0151	0	2	0	0
DAL2910-1547360817-airline-0448	AAL1164-1547360814-airline-0358	0	1	1	1
DAL2910-1547360817-airline-0448	AAL1164-1547360814-airline-0358	0	2	1	1
DAL2910-1547360817-airline-0448	AAL1476-1547360814-airline-0413	0	3	0	0
DAL2914-1547360817-airline-0077	AAL1490-1547360814-airline-0509	1	1	0	1
DAL2914-1547360817-airline-0077	AAL1490-1547360814-airline-0509	1	3	0	1
DAL2914-1547447163-airline-0360	AAL1490-1547447160-airline-0408	1	1	1	1
DAL2914-1547447163-airline-0360	AAL1490-1547447160-airline-0408	1	2	0	1
DAL2914-1547447163-airline-0360	AAL1490-1547447160-airline-0408	1	3	0	1
DAL2921-1547447163-airline-0406	AAL1489-1547447160-airline-0227	1	2	1	1
DAL2921-1547447163-airline-0406	AAL1489-1547447160-airline-0227	1	3	1	1
DAL2922-1547619946-airline-0429	AAL1174-1547619942-airline-0025	1	1	0	1
DAL2922-1547619946-airline-0429	AAL1174-1547619942-airline-0025	1	1	0	1
DAL64-1547274359-airline-0346	AAL1631-1547274356-airline-0056	1	1	0	1
DAL64-1547274359-airline-0346	AAL1631-1547274356-airline-0056	1	2	0	1
DAL75-1547447163-airline-0308	AAL1489-1547447160-airline-0227	0	1	1	0
DAL83-1547360817-airline-0135	AAL1490-1547360814-airline-0509	1	2	0	1
DAL83-1547360817-airline-0135	AAL1490-1547360814-airline-0509	1	3	0	1

ac1	ac2	target	type	option	mix
DAL830-1547360818-airline-0014	AAL1669-1547360814-airline-0615	0	2	1	0
DAL85-1547447163-airline-0258	AAL1172-1547447160-airline-0278	0	1	0	1
DAL85-1547447163-airline-0258	AAL1172-1547447160-airline-0278	0	3	1	1
DAL881-1547360818-airline-0085	AAL1631-1547360814-airline-0222	1	1	0	1
DAL881-1547360818-airline-0085	AAL1631-1547360814-airline-0222	1	2	0	1
DAL881-1547360818-airline-0085	AAL1631-1547360814-airline-0222	1	3	0	1
DAL887-1547360818-airline-0058	AAL1172-1547360814-airline-0425	1	3	0	0
DAL90-1547533576-airline-0526	AAL1172-1547533573-airline-0084	0	1	1	1
DAL90-1547533576-airline-0526	AAL1172-1547533573-airline-0084	0	2	1	1
DAL90-1547533576-airline-0526	AAL1172-1547533573-airline-0084	0	3	1	1
DAL9834-1547623914-22-3-159	AAL1471-1547360821-airline-0418	0	3	1	0
DAL9937-1547728010-1-0-243	AAL1164-1547533573-airline-0091	1	1	0	1
DAL9937-1547728010-1-0-243	AAL1164-1547533573-airline-0091	0	2	1	1
DAL9937-1547728010-1-0-243	AAL1164-1547533573-airline-0091	0	3	1	1
EDV5027-1547360826-airline-0186	AAL1172-1547360814-airline-0425	0	1	0	1
EDV5027-1547360826-airline-0186	AAL1172-1547360814-airline-0425	0	2	1	1
EDV5027-1547360826-airline-0186	AAL1172-1547360814-airline-0425	1	3	1	1
EDV5027-1547533574-airline-0148	AAL1164-1547533573-airline-0006	1	3	0	0
EDV5036-1547533574-airline-0088	AAL1172-1547533573-airline-0084	0	1	1	1

ac1	ac2	target	type	option	mix
EDV5036-1547533574-airline-0088	AAL1172-1547533573-airline-0084	0	2	1	1
EDV5036-1547533574-airline-0088	AAL1172-1547533573-airline-0084	1	3	1	1
EDV5036-1547533574-airline-0088	AAL1172-1547533573-airline-0084	0	3	1	1
EDV5047-1547360826-airline-0218	AAL1002-1547360814-airline-0446	0	1	0	1
EDV5047-1547360826-airline-0218	AAL1002-1547360814-airline-0446	0	2	1	1
EDV5109-1547360820-airline-0017	AAL1155-1547360814-airline-0355	1	3	0	0
EDV5340-1547447163-airline-0382	AAL1746-1547447160-airline-0171	0	1	1	0
EJA387-1547442334-3-4-220	AAL1159-1547274356-airline-0484	0	2	1	1
EJA387-1547442334-3-4-220	AAL1159-1547274356-airline-0484	0	3	1	1
EJA547-1547665562-3-1-96	AAL1164-1547533573-airline-0006	0	2	1	0
EJA547-1547665562-3-1-96	AAL1476-1547533573-airline-0608	1	2	1	0
EJA782-1547427959-0-0-39	AAL1076-1547274356-airline-0108	1	1	1	1
EJA782-1547427959-0-0-39	AAL1076-1547274356-airline-0108	1	3	1	1
EJA782-1547427959-0-0-39	AAL1076-1547274356-airline-0108	1	3	0	1
ENY3416-1547360814-airline-0316	AAL1476-1547360814-airline-0413	1	2	1	1
ENY3416-1547360814-airline-0316	AAL1476-1547360814-airline-0413	1	3	1	1
ENY3448-1547360814-airline-0304	AAL1638-1547360814-airline-0356	1	3	0	0
ENY3560-1547360814-airline-0588	AAL1631-1547360814-airline-0222	0	2	1	0
ENY3565-1547360820-airline-0001	AAL1638-1547360814-airline-0356	1	1	1	0

ac1	ac2	target	type	option	mix
ENY3630-1547360814-airline-0172	AAL1155-1547360814-airline-0355	1	2	1	0
ENY3630-1547360814-airline-0172	AAL1240-1547360814-airline-0036	1	3	0	0
ENY3638-1547360814-airline-0146	AAL1495-1547360821-airline-0365	0	1	0	0
ENY3638-1547360814-airline-0146	AAL1638-1547360814-airline-0356	0	1	1	0
ENY3731-1547533573-airline-0153	AAL1172-1547533573-airline-0084	0	1	1	1
ENY3731-1547533573-airline-0153	AAL1172-1547533573-airline-0084	0	2	1	1
ENY3731-1547533573-airline-0153	AAL1172-1547533573-airline-0084	0	3	1	1
ENY3798-1547533573-airline-0632	AAL1155-1547533573-airline-0290	1	1	1	1
ENY3798-1547533573-airline-0632	AAL1155-1547533573-airline-0290	1	3	1	1
ENY3807-1547533573-airline-0662	AAL1155-1547533573-airline-0290	1	1	1	1
ENY3807-1547533573-airline-0662	AAL1155-1547533573-airline-0290	1	2	1	1
FDX1324-1547698720-21-0-174	AAL1155-1547533573-airline-0290	1	2	1	1
FDX1324-1547698720-21-0-174	AAL1155-1547533573-airline-0290	1	3	1	1
FDX1410-1547545720-5-0-242	AAL1471-1547360821-airline-0418	1	3	0	0
FDX1439-1547461128-1-0-19	AAL1500-1547360814-airline-0316	0	1	1	1
FDX1439-1547461128-1-0-19	AAL1500-1547360814-airline-0316	0	2	0	1
FDX1439-1547461128-1-0-19	AAL1500-1547360814-airline-0316	0	3	0	1
FDX1454-1547461132-3-0-32	AAL1500-1547360814-airline-0316	1	2	0	1
FDX1454-1547461132-3-0-32	AAL1500-1547360814-airline-0316	0	2	0	1

ac1	ac2	target	type	option	mix
FDX1483-1547461117-11-0-58	AAL1654-1547367925-airline-0066	1	2	0	0
FDX1542-1547462964-1-0-102	AAL1500-1547360814-airline-0316	0	1	1	0
FDX1558-1547473714-0-2-117	AAL1638-1547360814-airline-0356	0	1	1	1
FDX1558-1547473714-0-2-117	AAL1638-1547360814-airline-0356	0	2	1	1
FDX1558-1547473714-0-2-117	AAL1638-1547360814-airline-0356	0	3	1	1
FDX447-1547560128-2-0-215	AAL1495-1547447166-airline-0321	1	3	0	0
FDX458-1547738326-37-0-225	AAL1478-1547619942-airline-0299	1	2	1	1
FDX458-1547738326-37-0-225	AAL1478-1547619942-airline-0299	1	3	1	1
FDX55-1547548251-9-3-0	AAL1638-1547360814-airline-0356	0	1	1	1
FDX55-1547548251-9-3-0	AAL1638-1547360814-airline-0356	0	3	0	1
FDX760-1547592536-8-0-219	AAL1172-1547447160-airline-0278	1	1	1	0
FFT1061-1547274360-airline-0356	AAL1155-1547274356-airline-0430	1	2	0	0
FFT2040-1547533577-airline-0253	AAL147-1547533579-airline-0037	0	2	0	1
FFT2040-1547533577-airline-0253	AAL147-1547533579-airline-0037	0	3	0	1
FFT2195-1547533577-airline-0214	AAL1159-1547533573-airline-0327	0	1	1	1
FFT2195-1547533577-airline-0214	AAL1159-1547533573-airline-0327	1	2	0	1
FFT2526-1547274360-airline-0206	AAL1631-1547274356-airline-0056	0	1	1	1
FFT2526-1547274360-airline-0206	AAL1631-1547274356-airline-0056	0	2	0	1
FFT474-1547447164-airline-0114	AAL1166-1547447160-airline-0300	1	2	0	0

ac1	ac2	target	type	option	mix
FFT489-1547447164-airline-0119	AAL1166-1547447160-airline-0300	1	3	1	0
FFT64-1547360819-airline-0125	AAL1002-1547360814-airline-0446	1	3	0	0
FFT81-1547533577-airline-0191	AAL1172-1547533573-airline-0084	1	1	0	1
FFT81-1547533577-airline-0191	AAL1172-1547533573-airline-0084	1	1	0	1
FFT81-1547533577-airline-0191	AAL1172-1547533573-airline-0084	1	3	1	1
FLE802-1547533577-airline-0212	AAL1476-1547533573-airline-0608	1	3	0	0
GAJ805-1547686811-1-1-161	AAL1159-1547533573-airline-0327	0	1	1	0
GEC8220-1547511767-3-0-151	AAL1159-1547274356-airline-0484	0	2	1	0
GTI565-1547789639-0-0-152	AAL1638-1547619942-airline-0465	0	1	0	0
JBU1251-1547619945-airline-0263	AAL1495-1547619949-airline-0065	1	2	1	0
JBU1295-1547533577-airline-0328	AAL1155-1547533573-airline-0290	1	3	0	0
JBU1295-1547533577-airline-0328	AAL147-1547533579-airline-0037	0	1	1	1
JBU1295-1547533577-airline-0328	AAL147-1547533579-airline-0037	0	3	1	1
JBU1392-1547360818-airline-0252	AAL1638-1547360814-airline-0356	1	2	0	0
JBU1392-1547619947-airline-0469	AAL1638-1547619942-airline-0465	1	2	0	1
JBU1392-1547619947-airline-0469	AAL1638-1547619942-airline-0465	1	3	0	1
JBU163-1547619945-airline-0450	AAL1495-1547619949-airline-0065	0	2	0	0
JBU1865-1547360818-airline-0157	AAL1159-1547360814-airline-0338	1	2	1	1
JBU1865-1547360818-airline-0157	AAL1159-1547360814-airline-0338	1	3	1	1

ac1	ac2	target	type	option	mix
JBU484-1547360816-airline-0048	AAL1159-1547360814-airline-0338	1	1	1	1
JBU484-1547360816-airline-0048	AAL1159-1547360814-airline-0338	1	2	0	1
JBU484-1547360816-airline-0048	AAL1159-1547360814-airline-0338	1	3	0	1
JBU566-1547274358-airline-0031	AAL1164-1547274356-airline-0307	0	3	0	0
JBU566-1547360816-airline-0000	AAL1240-1547360814-airline-0036	1	1	0	0
JBU566-1547533574-airline-0038	AAL1155-1547533573-airline-0290	1	3	0	0
JBU658-1547360816-airline-0210	AAL1240-1547360814-airline-0036	1	2	1	1
JBU658-1547360816-airline-0210	AAL1240-1547360814-airline-0036	1	2	1	1
JBU658-1547360816-airline-0210	AAL1240-1547360814-airline-0036	1	3	0	1
JBU720-1547360816-airline-0168	AAL1785-1547360814-airline-0360	1	1	0	1
JBU720-1547360816-airline-0168	AAL1785-1547360814-airline-0360	0	3	0	1
JBU801-1547360816-airline-0194	AAL1155-1547360814-airline-0355	1	1	0	0
JBU801-1547533574-airline-0360	AAL1155-1547533573-airline-0290	1	2	0	1
JBU801-1547533574-airline-0360	AAL1155-1547533573-airline-0290	1	2	0	1
JIA5104-1547533573-airline-0362	AAL147-1547533579-airline-0037	0	1	1	1
JIA5104-1547533573-airline-0362	AAL147-1547533579-airline-0037	0	2	0	1
JIA5104-1547533573-airline-0362	AAL147-1547533579-airline-0037	0	3	1	1
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	1	0	1
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	1	1	1

ac1	ac2	target	type	option	mix
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	2	1	1
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	3	1	1
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	3	1	1
JIA5106-1547360814-airline-0155	AAL1002-1547360814-airline-0446	0	3	1	1
JIA5114-1547360814-airline-0410	AAL1159-1547360814-airline-0338	0	2	1	1
JIA5114-1547360814-airline-0410	AAL1159-1547360814-airline-0338	0	3	1	1
JIA5399-1547360814-airline-0186	AAL1159-1547360814-airline-0338	0	2	1	1
JIA5399-1547360814-airline-0186	AAL1159-1547360814-airline-0338	0	3	0	1
JIA5620-1547447160-airline-0158	AAL1500-1547447160-airline-0076	1	1	1	0
JIA9912-1547757177-31-0-87	AAL1164-1547533573-airline-0091	1	2	1	1
JIA9912-1547757177-31-0-87	AAL1164-1547533573-airline-0091	0	2	0	1
LJY477-1547501297-dlad-6210899	AAL1164-1547360814-airline-0358	1	3	1	1
LJY477-1547501297-dlad-6210899	AAL1164-1547360814-airline-0358	1	3	0	1
LJY477-1547501297-dlad-6210899	AAL1476-1547360814-airline-0413	1	1	0	1
LJY477-1547501297-dlad-6210899	AAL1476-1547360814-airline-0413	1	1	0	1
LXJ454-1547494219-4-1-29	AAL1002-1547360814-airline-0446	0	3	1	1
LXJ454-1547494219-4-1-29	AAL1002-1547360814-airline-0446	0	3	1	1
LXJ549-1547540437-1-0-106	AAL1495-1547360821-airline-0365	1	1	0	1
LXJ549-1547540437-1-0-106	AAL1495-1547360821-airline-0365	1	2	1	1

ac1	ac2	target	type	option	mix
LXJ549-1547540437-1-0-106	AAL1495-1547360821-airline-0365	1	3	1	1
LXJ549-1547540437-1-0-106	AAL1495-1547360821-airline-0365	1	3	0	1
LXJ551-1547755646-1-0-107	AAL147-1547533579-airline-0037	1	3	1	0
N109MJ-1547737622-dlad-6218228	AAL1166-1547619942-airline-0541	1	2	1	1
N109MJ-1547737622-dlad-6218228	AAL1166-1547619942-airline-0541	1	3	1	1
N222JE-1547488790-4-1-107	AAL1495-1547360821-airline-0365	1	3	0	0
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	1	0	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	1	0	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	1	1	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	2	1	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	3	1	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	3	0	1
N454FX-1547759189-0-0-61	AAL147-1547533579-airline-0037	1	3	0	1
N549PA-1547779415-5-1-115	AAL1478-1547619942-airline-0299	1	1	1	1
N549PA-1547779415-5-1-115	AAL1478-1547619942-airline-0299	1	2	1	1
N549PA-1547779415-5-1-115	AAL1478-1547619942-airline-0299	1	3	1	1
N833JS-1547757852-1-0-47	AAL1159-1547533573-airline-0327	1	1	0	1
N833JS-1547757852-1-0-47	AAL1159-1547533573-airline-0327	1	3	0	1
N99AT-1547657987-7-0-97	AAL1159-1547447160-airline-0130	1	1	1	1

ac1	ac2	target	type	option	mix
N99AT-1547657987-7-0-97	AAL1159-1547447160-airline-0130	1	3	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	1	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	1	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	1	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	2	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	2	0	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	2	0	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	2	0	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	3	1	1
NKS1159-1547360823-airline-0358	AAL1240-1547360814-airline-0036	0	3	0	1
NKS286-1547533581-airline-0215	AAL1164-1547533573-airline-0006	1	2	0	1
NKS286-1547533581-airline-0215	AAL1164-1547533573-airline-0006	1	3	0	1
NKS286-1547619951-airline-0266	AAL1476-1547619942-airline-0544	0	1	1	0
NKS363-1547447168-airline-0050	AAL1495-1547447166-airline-0321	1	3	0	0
NKS606-1547447168-airline-0171	AAL1495-1547447166-airline-0321	1	3	1	0
NKS627-1547274364-airline-0335	AAL1159-1547274356-airline-0484	0	1	1	0
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	1	0	1
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	1	0	1
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	2	1	1

ac1	ac2	target	type	option	mix
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	2	0	1
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	3	0	1
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	3	0	1
NKS636-1547447168-airline-0247	AAL1159-1547447160-airline-0130	1	3	0	1
NKS643-1547447168-airline-0293	AAL1166-1547447160-airline-0300	1	3	0	0
NKS643-1547447168-airline-0293	AAL1495-1547447166-airline-0321	1	2	1	0
NKS845-1547533581-airline-0062	AAL1159-1547533573-airline-0327	0	3	1	0
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	1	2	1	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	2	0	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	2	0	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	1	3	1	1
NKS845-1547533581-airline-0062	AAL1164-1547533573-airline-0091	0	3	1	1
NKS943-1547619951-airline-0446	AAL1495-1547619949-airline-0065	1	2	1	0
NKS943-1547619951-airline-0446	AAL1638-1547619942-airline-0465	1	2	0	1
NKS943-1547619951-airline-0446	AAL1638-1547619942-airline-0465	0	2	0	1
PDT5009-1547533573-airline-0008	AAL147-1547533579-airline-0037	1	3	0	0
ROU1659-1547274356-airline-0109	AAL1164-1547274356-airline-0307	0	1	1	0
ROU1665-1547274356-airline-0213	AAL1164-1547274356-airline-0307	0	2	1	1
ROU1665-1547274356-airline-0213	AAL1164-1547274356-airline-0307	0	3	1	1

ac1	ac2	target	type	option	mix
ROU1741-1547274356-airline-0209	AAL1155-1547274356-airline-0430	1	2	1	0
ROU1741-1547533573-airline-0239	AAL1155-1547533573-airline-0290	1	1	1	0
ROU1741-1547533573-airline-0239	AAL1240-1547533573-airline-0111	1	1	0	1
ROU1741-1547533573-airline-0239	AAL1240-1547533573-airline-0111	0	2	0	1
ROU1818-1547533573-airline-0163	AAL1164-1547533573-airline-0006	1	2	0	1
ROU1818-1547533573-airline-0163	AAL1164-1547533573-airline-0006	1	2	0	1
RPA3416-1547274367-airline-0381	AAL1164-1547274356-airline-0307	1	2	1	1
RPA3416-1547274367-airline-0381	AAL1164-1547274356-airline-0307	1	3	1	1
RPA4391-1547533573-airline-0261	AAL1155-1547533573-airline-0290	1	3	1	0
RPA4627-1547533573-airline-0123	AAL1164-1547533573-airline-0091	1	1	0	0
RPA4629-1547619942-airline-0715	AAL145-1547619949-airline-0330	0	2	1	1
RPA4629-1547619942-airline-0715	AAL145-1547619949-airline-0330	0	3	1	1
RPA4646-1547360814-airline-0655	AAL1490-1547360814-airline-0509	1	2	0	0
SKW3805-1547447172-airline-0304	AAL1746-1547447160-airline-0171	0	1	1	1
SKW3805-1547447172-airline-0304	AAL1746-1547447160-airline-0171	0	2	1	1
SKW3805-1547447172-airline-0304	AAL1746-1547447160-airline-0171	0	3	1	1
SKW3805-1547447172-airline-0304	AAL1746-1547447160-airline-0171	0	3	1	1
SKW3903-1547533576-airline-0461	AAL1159-1547533573-airline-0327	0	2	1	1
SKW3903-1547533576-airline-0461	AAL1159-1547533573-airline-0327	1	3	1	1

ac1	ac2	target	type	option	mix
SKW5210-1547274356-airline-0030	AAL1076-1547274356-airline-0108	1	3	1	0
SKW5210-1547274356-airline-0030	AAL1155-1547274356-airline-0430	1	3	0	0
SKW5544-1547533573-airline-0067	AAL1172-1547533573-airline-0084	0	3	0	0
SWA1002-1547360826-airline-0321	AAL1164-1547360814-airline-0358	1	1	1	0
SWA1002-1547447172-airline-0060	AAL1166-1547447160-airline-0300	0	2	1	1
SWA1002-1547447172-airline-0060	AAL1166-1547447160-airline-0300	0	3	1	1
SWA1002-1547533585-airline-0112	AAL1164-1547533573-airline-0006	1	1	1	1
SWA1002-1547533585-airline-0112	AAL1164-1547533573-airline-0006	1	3	0	1
SWA106-1547533585-airline-0338	AAL1164-1547533573-airline-0006	0	3	0	0
SWA107-1547274368-airline-0596	AAL1159-1547274356-airline-0484	1	3	0	0
SWA107-1547533585-airline-0545	AAL1159-1547533573-airline-0327	1	2	1	0
SWA1292-1547447172-airline-0702	AAL1166-1547447160-airline-0300	1	2	1	1
SWA1292-1547447172-airline-0702	AAL1166-1547447160-airline-0300	1	2	1	1
SWA1292-1547619955-airline-0320	AAL1166-1547619942-airline-0541	1	2	0	1
SWA1292-1547619955-airline-0320	AAL1166-1547619942-airline-0541	1	3	0	1
SWA1294-1547447172-airline-0147	AAL1495-1547447166-airline-0321	0	2	1	1
SWA1294-1547447172-airline-0147	AAL1495-1547447166-airline-0321	0	3	0	1
SWA1305-1547360826-airline-0114	AAL1002-1547360814-airline-0446	1	1	0	1
SWA1305-1547360826-airline-0114	AAL1002-1547360814-airline-0446	1	2	0	1

ac1	ac2	target	type	option	mix
SWA1310-1547533585-airline-0702	AAL1159-1547533573-airline-0327	1	1	0	1
SWA1310-1547533585-airline-0702	AAL1159-1547533573-airline-0327	0	3	1	1
SWA1323-1547533585-airline-0543	AAL1076-1547533573-airline-0151	0	1	1	1
SWA1323-1547533585-airline-0543	AAL1076-1547533573-airline-0151	0	2	0	1
SWA1323-1547533585-airline-0543	AAL1076-1547533573-airline-0151	0	3	1	1
SWA1323-1547533585-airline-0543	AAL1076-1547533573-airline-0151	0	3	1	1
SWA1936-1547447172-airline-0298	AAL1159-1547447160-airline-0130	1	1	1	0
SWA1939-1547447172-airline-1033	AAL1172-1547447160-airline-0278	0	1	0	1
SWA1939-1547447172-airline-1033	AAL1172-1547447160-airline-0278	0	3	0	1
SWA2032-1547533585-airline-0592	AAL1164-1547533573-airline-0006	1	3	0	0
SWA2072-1547447172-airline-1057	AAL1166-1547447160-airline-0300	1	1	0	1
SWA2072-1547447172-airline-1057	AAL1166-1547447160-airline-0300	1	3	0	1
SWA2115-1547360826-airline-0950	AAL1172-1547360814-airline-0425	0	1	1	1
SWA2115-1547360826-airline-0950	AAL1172-1547360814-airline-0425	0	2	1	1
SWA2115-1547360826-airline-0950	AAL1172-1547360814-airline-0425	0	2	0	1
SWA2115-1547360826-airline-0950	AAL1172-1547360814-airline-0425	0	3	1	1
SWA2118-1547533585-airline-0823	AAL1240-1547533573-airline-0111	0	1	0	0
SWA34-1547447172-airline-0654	AAL1638-1547447160-airline-0492	1	1	0	1
SWA34-1547447172-airline-0654	AAL1638-1547447160-airline-0492	1	3	1	1

ac1	ac2	target	type	option	mix
SWA426-1547533585-airline-0184	AAL1159-1547533573-airline-0327	1	1	1	0
SWA428-1547274368-airline-0132	AAL1076-1547274356-airline-0108	1	1	1	1
SWA428-1547274368-airline-0132	AAL1076-1547274356-airline-0108	1	2	1	1
SWA428-1547274368-airline-0132	AAL1076-1547274356-airline-0108	1	3	1	1
SWA445-1547447172-airline-0599	AAL1495-1547447166-airline-0321	1	1	0	1
SWA445-1547447172-airline-0599	AAL1495-1547447166-airline-0321	1	2	0	1
SWA491-1547360826-airline-0226	AAL1490-1547360814-airline-0509	0	2	1	0
SWA505-1547533585-airline-0870	AAL147-1547533579-airline-0037	0	3	0	0
SWA5963-1547360826-airline-0004	AAL1495-1547360821-airline-0365	1	2	0	0
SWA744-1547360826-airline-0548	AAL1638-1547360814-airline-0356	1	3	0	0
SWA754-1547619955-airline-0620	AAL1495-1547619949-airline-0065	1	2	0	0
SWA754-1547619955-airline-0620	AAL1638-1547619942-airline-0465	0	1	0	1
SWA754-1547619955-airline-0620	AAL1638-1547619942-airline-0465	0	2	1	1
SWA754-1547619955-airline-0620	AAL1638-1547619942-airline-0465	1	3	1	1
SWA825-1547360826-airline-0146	AAL1155-1547360814-airline-0355	1	2	0	1
SWA825-1547360826-airline-0146	AAL1155-1547360814-airline-0355	1	3	0	1
SWA898-1547360826-airline-0623	AAL1155-1547360814-airline-0355	1	3	0	0
SWG398-1547274368-airline-0220	AAL1159-1547274356-airline-0484	0	1	0	1
SWG398-1547274368-airline-0220	AAL1159-1547274356-airline-0484	0	1	1	1

ac1	ac2	target	type	option	mix
SWG725-1547447172-airline-0079	AAL1159-1547447160-airline-0130	0	1	1	0
UAL1050-1547447171-airline-0149	AAL1500-1547447160-airline-0076	0	2	1	1
UAL1050-1547447171-airline-0149	AAL1500-1547447160-airline-0076	0	3	1	1
UAL1222-1547447171-airline-0165	AAL1159-1547447160-airline-0130	0	3	0	0
UAL1239-1547360825-airline-0130	AAL1164-1547360814-airline-0358	0	1	1	1
UAL1239-1547360825-airline-0130	AAL1164-1547360814-airline-0358	0	2	1	1
UAL1239-1547360825-airline-0130	AAL1164-1547360814-airline-0358	0	3	0	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	1	1	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	1	1	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	2	1	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	2	1	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	0	2	0	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	0	2	0	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	2	0	1
UAL1528-1547360104-fa-0003	AAL1164-1547360814-airline-0358	1	3	1	1
UAL1534-1547446537-fa-0008	AAL1166-1547447160-airline-0300	1	1	0	1
UAL1534-1547446537-fa-0008	AAL1166-1547447160-airline-0300	1	3	1	1
UAL1534-1547446537-fa-0008	AAL1166-1547447160-airline-0300	1	3	0	1
UAL1612-1547274367-airline-0352	AAL1159-1547274356-airline-0484	0	3	1	0

ac1	ac2	target	type	option	mix
UAL1827-1547274367-airline-0218	AAL1164-1547274356-airline-0307	0	1	1	1
UAL1827-1547274367-airline-0218	AAL1164-1547274356-airline-0307	0	3	1	1
UAL1851-1547360825-airline-0542	AAL147-1547360821-airline-0205	0	1	0	1
UAL1851-1547360825-airline-0542	AAL147-1547360821-airline-0205	0	2	1	1
UAL1851-1547360825-airline-0542	AAL147-1547360821-airline-0205	0	3	1	1
UAL1857-1547257928-fa-0002	AAL147-1547274355-airline-0025	1	1	0	1
UAL1857-1547257928-fa-0002	AAL147-1547274355-airline-0025	0	3	1	1
UAL1925-1547503335-fa-0006	AAL1164-1547533573-airline-0091	0	2	0	0
UAL2259-1547360825-airline-0223	AAL1172-1547360814-airline-0425	0	2	1	1
UAL2259-1547360825-airline-0223	AAL1172-1547360814-airline-0425	0	3	0	1
UAL2267-1547360825-airline-0207	AAL1476-1547360814-airline-0413	1	2	1	0
UAL2740-1547583556-fa-0000	AAL147-1547360821-airline-0205	0	1	1	1
UAL2740-1547583556-fa-0000	AAL147-1547360821-airline-0205	0	2	0	1
UCA4941-1547274366-airline-0348	AAL147-1547274355-airline-0025	0	2	1	1
UCA4941-1547274366-airline-0348	AAL147-1547274355-airline-0025	0	3	1	1
UPS1302-1547573556-3-0-52	AAL1471-1547360821-airline-0418	0	1	1	1
UPS1302-1547573556-3-0-52	AAL1471-1547360821-airline-0418	0	1	1	1
UPS1302-1547573556-3-0-52	AAL1471-1547360821-airline-0418	0	2	1	1
UPS1302-1547573556-3-0-52	AAL1471-1547360821-airline-0418	0	3	1	1

ac1	ac2	target	type	option	mix
UPS1351-1547552859-0-0-96	AAL1155-1547360814-airline-0355	1	2	1	1
UPS1351-1547552859-0-0-96	AAL1155-1547360814-airline-0355	1	3	1	1
VOI894-1547533586-airline-0389	AAL1155-1547533573-airline-0290	1	1	1	0
VOI894-1547533586-airline-0389	AAL147-1547533579-airline-0037	0	1	0	1
VOI894-1547533586-airline-0389	AAL147-1547533579-airline-0037	0	3	1	1
WJA2598-1547360826-airline-0378	AAL1166-1547360814-airline-0432	1	1	0	1
WJA2598-1547360826-airline-0378	AAL1166-1547360814-airline-0432	1	2	1	1
XOJ780-1547538543-5-0-84	AAL1159-1547360814-airline-0338	1	1	0	1
XOJ780-1547538543-5-0-84	AAL1159-1547360814-airline-0338	1	2	1	1
XOJ780-1547538543-5-0-84	AAL1159-1547360814-airline-0338	1	2	0	1
XOJ780-1547538543-5-0-84	AAL1159-1547360814-airline-0338	1	3	1	1
XOJ780-1547538543-5-0-84	AAL1159-1547360814-airline-0338	1	3	0	1

APPENDIX B
PART 2: SUPPLEMENTARY INFORMATION

This part of the Appendices includes supplementary information of Part 2. It includes a summary from applying the classification tree between the groups of aircraft conflicts from the qualitative comparison. The summary includes how the method separated the groups based on input flight contextual information on the prediction points of predicted aircraft conflict pairs.

B.1 Summary of the Identical Group vs. the Target Group

```
rpart(formula = qual ~ a_E1 + a_E2 + s_E1 + s_E2 + dec1 + ded1 +
    dcd1 + dec2 + ded2 + dcd2 + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + traf + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + spc, data = Data_i_t,
    method = "class")
  n= 284

          CP nsplit rel error    xerror       xstd
1 0.09408602      0 1.0000000 1.0000000 0.06740467
2 0.07661290      4 0.6209677 1.0000000 0.06740467
3 0.04032258      6 0.4677419 0.6532258 0.06136344
4 0.02016129      7 0.4274194 0.6612903 0.06158880
5 0.01000000     11 0.3467742 0.7177419 0.06304221

Variable importance
dec2 s_E2 dec1 a_E2 bcd2  pe2 bed2 ded2 bec2 bec1  pc2 s_E1 ded1 bed1 bcd1  pc1
```

```
  16   16   14   12    6    5    4    4    4    3    3    3    3    2    2    1
a_E1
   1

Node number 1: 284 observations,    complexity param=0.09408602
  predicted class=1  expected loss=0.4366197  P(node) =1
    class counts:   124   160
   probabilities: 0.437 0.563
  left son=2 (224 obs) right son=3 (60 obs)
  Primary splits:
      a_E2 < 107    to the right, improve=15.574860, (0 missing)
      s_E2 < 300    to the right, improve=15.574860, (0 missing)
      dec1 < 51.5   to the left,  improve=11.283810, (0 missing)
      bec1 < 4.5    to the right, improve= 6.397773, (0 missing)
      bec2 < 1.5    to the right, improve= 4.875886, (0 missing)
  Surrogate splits:
      s_E2 < 300    to the right, agree=0.993, adj=0.967, (0 split)
      pe2  < 1.5    to the right, agree=0.866, adj=0.367, (0 split)
      pc2  < 2.5    to the right, agree=0.824, adj=0.167, (0 split)
      ded2 < 5938   to the left,  agree=0.796, adj=0.033, (0 split)
      bcd2 < 0.5    to the right, agree=0.796, adj=0.033, (0 split)

Node number 2: 224 observations,    complexity param=0.09408602
  predicted class=0  expected loss=0.4776786  P(node) =0.7887324
    class counts:   117   107
   probabilities: 0.522 0.478
  left son=4 (213 obs) right son=5 (11 obs)
  Primary splits:
      dec2 < 6      to the right, improve=6.311997, (0 missing)
```

```
      dec1 < 51.5   to the left,  improve=5.755214, (0 missing)
      bec2 < 1.5    to the right, improve=4.865143, (0 missing)
      bcd2 < 4.5    to the left,  improve=4.723214, (0 missing)
      bed2 < 4.5    to the left,  improve=4.656096, (0 missing)
  Surrogate splits:
      ded2 < 179    to the right, agree=0.96, adj=0.182, (0 split)

Node number 3: 60 observations
  predicted class=1  expected loss=0.1166667  P(node) =0.2112676
    class counts:     7    53
   probabilities: 0.117 0.883

Node number 4: 213 observations,    complexity param=0.09408602
  predicted class=0  expected loss=0.4507042  P(node) =0.75
    class counts:   117    96
   probabilities: 0.549 0.451
  left son=8 (49 obs) right son=9 (164 obs)
  Primary splits:
      dec1 < 53     to the left,  improve=12.062350, (0 missing)
      bec2 < 1.5    to the right, improve= 5.583981, (0 missing)
      bec1 < 4.5    to the right, improve= 4.758236, (0 missing)
      bcd2 < 4.5    to the left,  improve= 4.732819, (0 missing)
      bed2 < 4.5    to the left,  improve= 4.576076, (0 missing)
  Surrogate splits:
      dec2 < 84     to the left,  agree=0.915, adj=0.633, (0 split)
      pc1  < 1.5    to the left,  agree=0.803, adj=0.143, (0 split)
      ded2 < 272.5  to the left,  agree=0.793, adj=0.102, (0 split)
      pe2  < 3.5    to the right, agree=0.789, adj=0.082, (0 split)
      ded1 < 4937.5 to the right, agree=0.779, adj=0.041, (0 split)
```

```
Node number 5: 11 observations
  predicted class=1  expected loss=0  P(node) =0.03873239
    class counts:     0    11
   probabilities: 0.000 1.000

Node number 8: 49 observations
  predicted class=0  expected loss=0.1428571  P(node) =0.1725352
    class counts:    42     7
   probabilities: 0.857 0.143

Node number 9: 164 observations,    complexity param=0.09408602
  predicted class=1  expected loss=0.4573171  P(node) =0.5774648
    class counts:    75    89
   probabilities: 0.457 0.543
  left son=18 (130 obs) right son=19 (34 obs)
  Primary splits:
      dec2 < 133.5  to the right, improve=9.897462, (0 missing)
      bed2 < 4.5    to the left,  improve=6.048753, (0 missing)
      bcd2 < 4.5    to the left,  improve=5.857593, (0 missing)
      s_E2 < 483.5  to the right, improve=5.434636, (0 missing)
      bec2 < 3.5    to the left,  improve=4.689497, (0 missing)
  Surrogate splits:
      dec1 < 119.5  to the right, agree=0.860, adj=0.324, (0 split)
      pc2  < 2.5    to the right, agree=0.841, adj=0.235, (0 split)
      a_E2 < 160    to the right, agree=0.811, adj=0.088, (0 split)
      s_E2 < 331.5  to the right, agree=0.811, adj=0.088, (0 split)
      ded2 < 312.5  to the right, agree=0.811, adj=0.088, (0 split)
```

```
Node number 18: 130 observations,    complexity param=0.0766129
  predicted class=0  expected loss=0.4538462  P(node) =0.4577465
    class counts:    71    59
   probabilities: 0.546 0.454
  left son=36 (19 obs) right son=37 (111 obs)
  Primary splits:
      dec1 < 136.5  to the left,  improve=7.164030, (0 missing)
      bed2 < 4.5    to the left,  improve=5.830253, (0 missing)
      bcd2 < 4.5    to the left,  improve=5.360385, (0 missing)
      bec2 < 3.5    to the left,  improve=5.037063, (0 missing)
      ded1 < 619    to the left,  improve=4.589011, (0 missing)
  Surrogate splits:
      dec2 < 178.5  to the left,  agree=0.900, adj=0.316, (0 split)
      ded1 < 445.5  to the left,  agree=0.892, adj=0.263, (0 split)
      ded2 < 349.5  to the left,  agree=0.869, adj=0.105, (0 split)
      a_E1 < 39.5   to the left,  agree=0.862, adj=0.053, (0 split)

Node number 19: 34 observations
  predicted class=1  expected loss=0.1176471  P(node) =0.1197183
    class counts:     4    30
   probabilities: 0.118 0.882

Node number 36: 19 observations
  predicted class=0  expected loss=0.05263158  P(node) =0.06690141
    class counts:    18     1
   probabilities: 0.947 0.053

Node number 37: 111 observations,    complexity param=0.0766129
  predicted class=1  expected loss=0.4774775  P(node) =0.3908451
```

```
   class counts:    53    58
  probabilities: 0.477 0.523
  left son=74 (58 obs) right son=75 (53 obs)
  Primary splits:
      bed2 < 4.5    to the left,  improve=4.982703, (0 missing)
      bec2 < 3.5    to the left,  improve=4.831325, (0 missing)
      bcd2 < 4.5    to the left,  improve=4.316608, (0 missing)
      a_E2 < 226.5  to the left,  improve=4.002772, (0 missing)
      s_E2 < 458    to the right, improve=2.286960, (0 missing)
  Surrogate splits:
      bec2 < 4.5    to the left,  agree=0.973, adj=0.943, (0 split)
      bcd2 < 4.5    to the left,  agree=0.973, adj=0.943, (0 split)
      s_E2 < 444    to the right, agree=0.838, adj=0.660, (0 split)
      a_E2 < 341.5  to the right, agree=0.721, adj=0.415, (0 split)
      bec1 < 3.5    to the left,  agree=0.631, adj=0.226, (0 split)

Node number 74: 58 observations,    complexity param=0.04032258
  predicted class=0  expected loss=0.3793103  P(node) =0.2042254
    class counts:    36    22
   probabilities: 0.621 0.379
  left son=148 (51 obs) right son=149 (7 obs)
  Primary splits:
      bcd2 < 1.5    to the right, improve=3.635275, (0 missing)
      a_E1 < 365    to the left,  improve=3.448078, (0 missing)
      bec2 < 1.5    to the right, improve=2.550345, (0 missing)
      bed2 < 1.5    to the right, improve=2.485345, (0 missing)
      a_E2 < 226.5  to the left,  improve=2.290737, (0 missing)
  Surrogate splits:
      bed2 < 1.5    to the right, agree=0.948, adj=0.571, (0 split)
```

```
      bec2 < 1.5    to the right, agree=0.914, adj=0.286, (0 split)

Node number 75: 53 observations,    complexity param=0.02016129
  predicted class=1  expected loss=0.3207547  P(node) =0.1866197
    class counts:    17    36
   probabilities: 0.321 0.679
  left son=150 (24 obs) right son=151 (29 obs)
  Primary splits:
      s_E2 < 403    to the left,  improve=2.818478, (0 missing)
      s_E1 < 435.5  to the right, improve=1.890831, (0 missing)
      dec2 < 229.5  to the right, improve=1.469778, (0 missing)
      bcd1 < 6.5    to the right, improve=1.123751, (0 missing)
      a_E1 < 212.5  to the right, improve=1.042052, (0 missing)
  Surrogate splits:
      ded2 < 974    to the left,  agree=0.717, adj=0.375, (0 split)
      ded1 < 1521.5 to the right, agree=0.660, adj=0.250, (0 split)
      ps2  < 0.5    to the right, agree=0.660, adj=0.250, (0 split)
      a_E1 < 223    to the left,  agree=0.642, adj=0.208, (0 split)
      dcd1 < 985.5  to the right, agree=0.642, adj=0.208, (0 split)

Node number 148: 51 observations,    complexity param=0.02016129
  predicted class=0  expected loss=0.3137255  P(node) =0.1795775
    class counts:    35    16
   probabilities: 0.686 0.314
  left son=296 (23 obs) right son=297 (28 obs)
  Primary splits:
      bec1 < 4      to the right, improve=2.814822, (0 missing)
      bed1 < 3.5    to the right, improve=2.814822, (0 missing)
      a_E1 < 365    to the left,  improve=2.563101, (0 missing)
```

```
      bcd1 < 3.5    to the right, improve=1.960784, (0 missing)
      s_E2 < 464.5  to the left,  improve=1.637803, (0 missing)
  Surrogate splits:
      bed1 < 3.5    to the right, agree=1.000, adj=1.000, (0 split)
      bcd1 < 3.5    to the right, agree=0.980, adj=0.957, (0 split)
      s_E1 < 453.5  to the left,  agree=0.804, adj=0.565, (0 split)
      ded1 < 1343.5 to the left,  agree=0.667, adj=0.261, (0 split)
      ded2 < 1192.5 to the left,  agree=0.667, adj=0.261, (0 split)

Node number 149: 7 observations
  predicted class=1  expected loss=0.1428571  P(node) =0.02464789
    class counts:     1     6
   probabilities: 0.143 0.857

Node number 150: 24 observations,    complexity param=0.02016129
  predicted class=0  expected loss=0.5  P(node) =0.08450704
    class counts:    12    12
   probabilities: 0.500 0.500
  left son=300 (7 obs) right son=301 (17 obs)
  Primary splits:
      s_E1 < 435.5  to the right, improve=2.521008, (0 missing)
      dcd2 < 475    to the right, improve=2.097902, (0 missing)
      s_E2 < 390    to the right, improve=1.500000, (0 missing)
      dec1 < 478    to the left,  improve=1.500000, (0 missing)
      dec2 < 485.5  to the left,  improve=1.500000, (0 missing)
  Surrogate splits:
      bec1 < 1.5    to the left,  agree=0.833, adj=0.429, (0 split)
      a_E1 < 365    to the right, agree=0.792, adj=0.286, (0 split)
      s_E2 < 399    to the right, agree=0.792, adj=0.286, (0 split)
```

```
     bed1 < 1.5    to the left,  agree=0.792, adj=0.286, (0 split)
     ded1 < 861.5  to the left,  agree=0.750, adj=0.143, (0 split)

Node number 151: 29 observations
  predicted class=1  expected loss=0.1724138  P(node) =0.1021127
    class counts:     5    24
   probabilities: 0.172 0.828

Node number 296: 23 observations
  predicted class=0  expected loss=0.1304348  P(node) =0.08098592
    class counts:    20     3
   probabilities: 0.870 0.130

Node number 297: 28 observations,    complexity param=0.02016129
  predicted class=0  expected loss=0.4642857  P(node) =0.09859155
    class counts:    15    13
   probabilities: 0.536 0.464
  left son=594 (11 obs) right son=595 (17 obs)
  Primary splits:
      s_E2 < 464.5  to the left,  improve=2.891138, (0 missing)
      ded2 < 1670.5 to the left,  improve=1.785714, (0 missing)
      dec1 < 285.5  to the left,  improve=1.554302, (0 missing)
      dec2 < 629.5  to the left,  improve=1.166667, (0 missing)
      a_E1 < 340    to the left,  improve=1.108059, (0 missing)
  Surrogate splits:
      a_E2 < 258.5  to the left,  agree=0.786, adj=0.455, (0 split)
      pe2  < 1.5    to the left,  agree=0.786, adj=0.455, (0 split)
      s_E1 < 354    to the left,  agree=0.714, adj=0.273, (0 split)
      dec1 < 190.5  to the left,  agree=0.679, adj=0.182, (0 split)
```

```
    ded1 < 1471   to the left,  agree=0.679, adj=0.182, (0 split)

Node number 300: 7 observations
  predicted class=0  expected loss=0.1428571  P(node) =0.02464789
    class counts:     6     1
   probabilities: 0.857 0.143

Node number 301: 17 observations
  predicted class=1  expected loss=0.3529412  P(node) =0.05985915
    class counts:     6    11
   probabilities: 0.353 0.647

Node number 594: 11 observations
  predicted class=0  expected loss=0.1818182  P(node) =0.03873239
    class counts:     9     2
   probabilities: 0.818 0.182

Node number 595: 17 observations
  predicted class=1  expected loss=0.3529412  P(node) =0.05985915
    class counts:     6    11
   probabilities: 0.353 0.647
```

B.2 Summary of the Identical Group vs. the Maneuver Group

```
rpart(formula = qual ~ a_E1 + a_E2 + s_E1 + s_E2 + dec1 + ded1 +
    dcd1 + dec2 + ded2 + dcd2 + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + traf + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + spc, data = Data_i_m,
    method = "class")
  n= 582
```

```
       CP nsplit rel error  xerror       xstd
1 0.03125      0    1.0000 1.00000 0.06731855
2 0.01875      2    0.9375 1.06875 0.06868114
3 0.01250      4    0.9000 1.14375 0.07000523
4 0.01000      5    0.8875 1.20625 0.07098588

Variable importance
dec2 dec1 a_E1  pe1  ps1 s_E1 a_E2 traf bed1 ded1 bcd1 ded2  pe2 s_E2 dcd1 bec1
  19   14   11    8    8    8    6    4    4    4    4    3    3    2    2    1

Node number 1: 582 observations,    complexity param=0.03125
  predicted class=0  expected loss=0.2749141  P(node) =1
    class counts:   422   160
   probabilities: 0.725 0.275
  left son=2 (486 obs) right son=3 (96 obs)
  Primary splits:
      dec2 < 394.5  to the left,  improve=6.881658, (0 missing)
      dec1 < 426.5  to the left,  improve=6.354240, (0 missing)
      ded2 < 3177.5 to the left,  improve=1.996362, (0 missing)
      spc  < 1.5    to the left,  improve=1.636729, (0 missing)
      ded1 < 4087   to the left,  improve=1.552031, (0 missing)
  Surrogate splits:
      dec1 < 554.5  to the left,  agree=0.936, adj=0.615, (0 split)
      s_E2 < 557.5  to the left,  agree=0.838, adj=0.021, (0 split)

Node number 2: 486 observations,    complexity param=0.01875
  predicted class=0  expected loss=0.2407407  P(node) =0.8350515
    class counts:   369   117
```

```
  probabilities: 0.759 0.241
 left son=4 (449 obs) right son=5 (37 obs)
 Primary splits:
     bed1 < 1.5    to the right, improve=2.171813, (0 missing)
     a_E1 < 199.5  to the left,  improve=2.087869, (0 missing)
     ded1 < 1483.5 to the right, improve=1.892212, (0 missing)
     dcd1 < 3959   to the left,  improve=1.861324, (0 missing)
     dec1 < 143.5  to the right, improve=1.843399, (0 missing)
 Surrogate splits:
     bcd1 < 1.5    to the right, agree=0.996, adj=0.946, (0 split)
     bec1 < 1.5    to the right, agree=0.940, adj=0.216, (0 split)
     ded2 < 140.5  to the right, agree=0.926, adj=0.027, (0 split)
     dcd2 < 139    to the right, agree=0.926, adj=0.027, (0 split)

Node number 3: 96 observations,    complexity param=0.03125
 predicted class=0  expected loss=0.4479167  P(node) =0.1649485
   class counts:    53    43
  probabilities: 0.552 0.448
 left son=6 (58 obs) right son=7 (38 obs)
 Primary splits:
     dec2 < 571.5  to the right, improve=4.243232, (0 missing)
     dec1 < 777.5  to the right, improve=3.068056, (0 missing)
     dcd1 < 890.5  to the left,  improve=2.515242, (0 missing)
     ded2 < 1951.5 to the right, improve=2.334722, (0 missing)
     pe1  < 2.5    to the right, improve=1.680572, (0 missing)
 Surrogate splits:
     dec1 < 650    to the right, agree=0.802, adj=0.500, (0 split)
     ded2 < 940    to the right, agree=0.771, adj=0.421, (0 split)
     s_E1 < 385.5  to the right, agree=0.729, adj=0.316, (0 split)
```

```
    ded1 < 1326   to the right, agree=0.708, adj=0.263, (0 split)
    a_E2 < 370.5  to the left,  agree=0.677, adj=0.184, (0 split)

Node number 4: 449 observations
  predicted class=0  expected loss=0.2271715  P(node) =0.7714777
    class counts:   347   102
   probabilities: 0.773 0.227

Node number 5: 37 observations,    complexity param=0.01875
  predicted class=0  expected loss=0.4054054  P(node) =0.06357388
    class counts:    22    15
   probabilities: 0.595 0.405
  left son=10 (17 obs) right son=11 (20 obs)
  Primary splits:
    a_E1 < 223    to the left,  improve=5.208426, (0 missing)
    pe1  < 1.5    to the left,  improve=3.995733, (0 missing)
    s_E1 < 484    to the left,  improve=3.523552, (0 missing)
    traf < 1.5    to the right, improve=3.299376, (0 missing)
    ps1  < 0.5    to the right, improve=2.966493, (0 missing)
  Surrogate splits:
    pe1  < 1.5    to the left,  agree=0.973, adj=0.941, (0 split)
    ps1  < 0.5    to the right, agree=0.946, adj=0.882, (0 split)
    s_E1 < 375.5  to the left,  agree=0.811, adj=0.588, (0 split)
    traf < 2.5    to the right, agree=0.757, adj=0.471, (0 split)
    dec1 < 141    to the right, agree=0.703, adj=0.353, (0 split)

Node number 6: 58 observations
  predicted class=0  expected loss=0.3275862  P(node) =0.09965636
    class counts:    39    19
```

```
   probabilities: 0.672 0.328

Node number 7: 38 observations
  predicted class=1  expected loss=0.3684211  P(node) =0.0652921
    class counts:    14    24
   probabilities: 0.368 0.632

Node number 10: 17 observations
  predicted class=0  expected loss=0.1176471  P(node) =0.02920962
    class counts:    15     2
   probabilities: 0.882 0.118

Node number 11: 20 observations,    complexity param=0.0125
  predicted class=1  expected loss=0.35  P(node) =0.03436426
    class counts:     7    13
   probabilities: 0.350 0.650
  left son=22 (10 obs) right son=23 (10 obs)
  Primary splits:
      a_E2 < 308.5  to the right, improve=2.5000000, (0 missing)
      ded1 < 1076   to the left,  improve=1.3828280, (0 missing)
      s_E1 < 484    to the left,  improve=0.9241758, (0 missing)
      dec1 < 215    to the left,  improve=0.9241758, (0 missing)
      dec2 < 186    to the left,  improve=0.9241758, (0 missing)
  Surrogate splits:
      pe2  < 2.5    to the right, agree=0.80, adj=0.6, (0 split)
      a_E1 < 368.5  to the right, agree=0.75, adj=0.5, (0 split)
      s_E2 < 462    to the right, agree=0.75, adj=0.5, (0 split)
      ded1 < 1799.5 to the left,  agree=0.70, adj=0.4, (0 split)
      dcd1 < 1670   to the left,  agree=0.70, adj=0.4, (0 split)
```

```
Node number 22: 10 observations
  predicted class=0  expected loss=0.4  P(node) =0.01718213
    class counts:     6     4
   probabilities: 0.600 0.400

Node number 23: 10 observations
  predicted class=1  expected loss=0.1  P(node) =0.01718213
    class counts:     1     9
   probabilities: 0.100 0.900
```

B.3 Summary of the Identical Group vs. the Different Group

```
rpart(formula = qual ~ a_E1 + a_E2 + s_E1 + s_E2 + dec1 + ded1 +
    dcd1 + dec2 + ded2 + dcd2 + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + traf + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + spc, data = Data_i_f,
    method = "class")
  n= 524

        CP nsplit rel error  xerror       xstd
1 0.262500      0   1.00000 1.00000 0.06589084
2 0.068750      1   0.73750 0.76250 0.06046545
3 0.040625      2   0.66875 0.70000 0.05865054
4 0.037500      6   0.50625 0.70625 0.05884025
5 0.031250      7   0.46875 0.65625 0.05726853
6 0.021875      8   0.43750 0.61250 0.05578690
7 0.010000     10   0.39375 0.52500 0.05249046

Variable importance
```

```
dec2 a_E2 s_E2 dec1 ded2 dcd2  pc2  pc1 dcd1 ded1 s_E1 bcd2  ps1  pe2
  29   19   19   14    5    3    2    2    1    1    1    1    1    1


Node number 1: 524 observations,    complexity param=0.2625
  predicted class=0  expected loss=0.3053435  P(node) =1
    class counts:   364   160
   probabilities: 0.695 0.305
  left son=2 (466 obs) right son=3 (58 obs)
  Primary splits:
      a_E2 < 74     to the right, improve=40.42830, (0 missing)
      s_E2 < 278.5  to the right, improve=40.20128, (0 missing)
      dec1 < 426    to the left,  improve=23.33659, (0 missing)
      pe2  < 1.5    to the right, improve=19.92357, (0 missing)
      pc2  < 2.5    to the right, improve=13.47785, (0 missing)
  Surrogate splits:
      s_E2 < 252.5  to the right, agree=0.996, adj=0.966, (0 split)
      bcd2 < 0.5    to the right, agree=0.893, adj=0.034, (0 split)

Node number 2: 466 observations,    complexity param=0.06875
  predicted class=0  expected loss=0.2360515  P(node) =0.889313
    class counts:   356   110
   probabilities: 0.764 0.236
  left son=4 (455 obs) right son=5 (11 obs)
  Primary splits:
      dec2 < 5      to the right, improve=13.149990, (0 missing)
      dec1 < 431    to the left,  improve= 9.746483, (0 missing)
      bec2 < 4.5    to the left,  improve= 6.531104, (0 missing)
      bcd2 < 4.5    to the left,  improve= 5.544233, (0 missing)
      bed2 < 4.5    to the left,  improve= 4.931632, (0 missing)
```

```
  Surrogate splits:
      ded2 < 176.5  to the right, agree=0.981, adj=0.182, (0 split)

Node number 3: 58 observations
  predicted class=1  expected loss=0.137931  P(node) =0.110687
    class counts:     8    50
   probabilities: 0.138 0.862

Node number 4: 455 observations,    complexity param=0.040625
  predicted class=0  expected loss=0.2175824  P(node) =0.8683206
    class counts:   356    99
   probabilities: 0.782 0.218
  left son=8 (401 obs) right son=9 (54 obs)
  Primary splits:
      dec1 < 431    to the left,  improve=11.097860, (0 missing)
      dec2 < 435    to the left,  improve= 5.370196, (0 missing)
      bcd2 < 4.5    to the left,  improve= 5.065816, (0 missing)
      bed2 < 4.5    to the left,  improve= 4.431889, (0 missing)
      bec1 < 4.5    to the right, improve= 4.123151, (0 missing)
  Surrogate splits:
      dec2 < 534    to the left,  agree=0.971, adj=0.759, (0 split)
      ded2 < 3975   to the left,  agree=0.892, adj=0.093, (0 split)
      s_E2 < 590.5  to the left,  agree=0.888, adj=0.056, (0 split)
      s_E1 < 624    to the left,  agree=0.886, adj=0.037, (0 split)
      dcd1 < 143.5  to the right, agree=0.886, adj=0.037, (0 split)

Node number 5: 11 observations
  predicted class=1  expected loss=0  P(node) =0.02099237
    class counts:     0    11
```

```
  probabilities: 0.000 1.000

Node number 8: 401 observations,    complexity param=0.040625
  predicted class=0  expected loss=0.1770574  P(node) =0.7652672
    class counts:   330    71
   probabilities: 0.823 0.177
  left son=16 (107 obs) right son=17 (294 obs)
  Primary splits:
      dec1 < 19     to the left,  improve=4.957798, (0 missing)
      bcd2 < 4.5    to the left,  improve=3.205017, (0 missing)
      bec1 < 4.5    to the right, improve=3.073396, (0 missing)
      bed2 < 4.5    to the left,  improve=2.983595, (0 missing)
      ded1 < 3321.5 to the left,  improve=2.931242, (0 missing)
  Surrogate splits:
      dec2 < 72.5   to the left,  agree=0.938, adj=0.766, (0 split)
      ded1 < 376    to the left,  agree=0.768, adj=0.131, (0 split)
      s_E1 < 509.5  to the right, agree=0.756, adj=0.084, (0 split)
      ded2 < 273    to the left,  agree=0.756, adj=0.084, (0 split)
      pe2  < 3.5    to the right, agree=0.753, adj=0.075, (0 split)

Node number 9: 54 observations,    complexity param=0.040625
  predicted class=1  expected loss=0.4814815  P(node) =0.1030534
    class counts:    26    28
   probabilities: 0.481 0.519
  left son=18 (40 obs) right son=19 (14 obs)
  Primary splits:
      dec2 < 567    to the right, improve=6.355820, (0 missing)
      ded2 < 1218   to the right, improve=6.355820, (0 missing)
      dcd2 < 629.5  to the right, improve=4.798190, (0 missing)
```

```
      s_E1 < 439    to the right, improve=4.629630, (0 missing)
      s_E2 < 480    to the right, improve=3.980451, (0 missing)
  Surrogate splits:
      ded2 < 864.5  to the right, agree=0.852, adj=0.429, (0 split)
      dec1 < 646    to the right, agree=0.815, adj=0.286, (0 split)
      dcd2 < 167.5  to the right, agree=0.815, adj=0.286, (0 split)
      a_E2 < 370.5  to the left,  agree=0.796, adj=0.214, (0 split)
      bec2 < 7.5    to the left,  agree=0.778, adj=0.143, (0 split)

Node number 16: 107 observations
  predicted class=0  expected loss=0.04672897  P(node) =0.2041985
    class counts:   102     5
   probabilities: 0.953 0.047

Node number 17: 294 observations,    complexity param=0.040625
  predicted class=0  expected loss=0.2244898  P(node) =0.5610687
    class counts:   228    66
   probabilities: 0.776 0.224
  left son=34 (248 obs) right son=35 (46 obs)
  Primary splits:
      dec2 < 106.5  to the right, improve=19.949390, (0 missing)
      bcd2 < 3.5    to the left,  improve= 6.899242, (0 missing)
      bed2 < 3.5    to the left,  improve= 6.859410, (0 missing)
      pc2  < 2.5    to the right, improve= 5.732081, (0 missing)
      bec2 < 3.5    to the left,  improve= 4.698002, (0 missing)
  Surrogate splits:
      pc2  < 2.5    to the right, agree=0.884, adj=0.261, (0 split)
      dec1 < 80.5   to the right, agree=0.878, adj=0.217, (0 split)
      pc1  < 1.5    to the right, agree=0.857, adj=0.087, (0 split)
```

```
     s_E2 < 278.5  to the right, agree=0.854, adj=0.065, (0 split)
     ded2 < 287.5  to the right, agree=0.854, adj=0.065, (0 split)

Node number 18: 40 observations,    complexity param=0.03125
  predicted class=0  expected loss=0.375  P(node) =0.07633588
    class counts:    25    15
   probabilities: 0.625 0.375
  left son=36 (23 obs) right son=37 (17 obs)
  Primary splits:
      dcd2 < 694    to the right, improve=4.376598, (0 missing)
      ded2 < 1218   to the right, improve=3.944805, (0 missing)
      a_E2 < 292    to the right, improve=2.916667, (0 missing)
      s_E2 < 480    to the right, improve=2.803333, (0 missing)
      a_E1 < 353    to the left,  improve=2.133838, (0 missing)
  Surrogate splits:
      ded2 < 1617   to the right, agree=0.85, adj=0.647, (0 split)
      dcd1 < 827.5  to the right, agree=0.80, adj=0.529, (0 split)
      ded1 < 1566.5 to the right, agree=0.75, adj=0.412, (0 split)
      s_E1 < 498.5  to the right, agree=0.70, adj=0.294, (0 split)
      ps1  < 0.5    to the left,  agree=0.70, adj=0.294, (0 split)

Node number 19: 14 observations
  predicted class=1  expected loss=0.07142857  P(node) =0.02671756
    class counts:     1    13
   probabilities: 0.071 0.929

Node number 34: 248 observations,    complexity param=0.021875
  predicted class=0  expected loss=0.1451613  P(node) =0.4732824
    class counts:   212    36
```

```
  probabilities: 0.855 0.145
 left son=68 (167 obs) right son=69 (81 obs)
 Primary splits:
     dec1 < 236.5  to the left,  improve=3.846310, (0 missing)
     bcd2 < 3.5    to the left,  improve=2.913511, (0 missing)
     bed2 < 3.5    to the left,  improve=2.694014, (0 missing)
     ded2 < 3472   to the left,  improve=2.081720, (0 missing)
     a_E2 < 356.5  to the right, improve=1.893252, (0 missing)
 Surrogate splits:
     dec2 < 314.5  to the left,  agree=0.831, adj=0.481, (0 split)

Node number 35: 46 observations,    complexity param=0.0375
  predicted class=1  expected loss=0.3478261  P(node) =0.08778626
    class counts:    16    30
   probabilities: 0.348 0.652
  left son=70 (12 obs) right son=71 (34 obs)
  Primary splits:
      dec1 < 61     to the left,  improve=5.251918, (0 missing)
      s_E2 < 381.5  to the right, improve=1.583561, (0 missing)
      a_E2 < 375    to the left,  improve=1.253950, (0 missing)
      ded2 < 1101.5 to the right, improve=1.220442, (0 missing)
      dcd2 < 1022.5 to the right, improve=1.220442, (0 missing)
  Surrogate splits:
      pc1  < 1.5    to the left,  agree=0.826, adj=0.333, (0 split)
      dec2 < 32     to the left,  agree=0.804, adj=0.250, (0 split)
      ded2 < 250.5  to the left,  agree=0.783, adj=0.167, (0 split)
      dcd2 < 213.5  to the left,  agree=0.783, adj=0.167, (0 split)
      pe2  < 3.5    to the right, agree=0.783, adj=0.167, (0 split)
```

```
Node number 36: 23 observations
  predicted class=0  expected loss=0.173913  P(node) =0.04389313
    class counts:    19     4
   probabilities: 0.826 0.174

Node number 37: 17 observations
  predicted class=1  expected loss=0.3529412  P(node) =0.03244275
    class counts:     6    11
   probabilities: 0.353 0.647

Node number 68: 167 observations
  predicted class=0  expected loss=0.08383234  P(node) =0.3187023
    class counts:   153    14
   probabilities: 0.916 0.084

Node number 69: 81 observations,    complexity param=0.021875
  predicted class=0  expected loss=0.2716049  P(node) =0.1545802
    class counts:    59    22
   probabilities: 0.728 0.272
  left son=138 (72 obs) right son=139 (9 obs)
  Primary splits:
      dec2 < 229.5  to the right, improve=7.716049, (0 missing)
      bec2 < 3.5    to the left,  improve=3.871605, (0 missing)
      bed2 < 3.5    to the left,  improve=3.871605, (0 missing)
      bcd2 < 3.5    to the left,  improve=3.523584, (0 missing)
      s_E2 < 482.5  to the right, improve=2.380452, (0 missing)

Node number 70: 12 observations
  predicted class=0  expected loss=0.25  P(node) =0.02290076
```

```
    class counts:     9     3
   probabilities: 0.750 0.250

Node number 71: 34 observations
  predicted class=1  expected loss=0.2058824  P(node) =0.0648855
    class counts:     7    27
   probabilities: 0.206 0.794

Node number 138: 72 observations
  predicted class=0  expected loss=0.1944444  P(node) =0.1374046
    class counts:    58    14
   probabilities: 0.806 0.194

Node number 139: 9 observations
  predicted class=1  expected loss=0.1111111  P(node) =0.01717557
    class counts:     1     8
   probabilities: 0.111 0.889
```

APPENDIX C
PART 3: SUPPLEMENTARY INFORMATION

This part of the Appendices includes supplementary information of Part 3. First, it includes a summary of general statistics on variables of the flight contextual information. Also, it includes summaries from applying three modeling methods to predict ATCo actions based on the extracted flight contextual information and categorized ATCo actions. The summaries include the results of each sub-models on three modeling methods. Additionally, the results of both regression and classification tree modeling methods include tree diagram to illustrate how the methods separated the input data based on the values of the flight contextual information.

C.1 Summary of General Statistics on the Flight Contextual Information

Table C.1.: A summary of general statistics on the continuous variables from the flight contextual information

Vars	Min	1st Qt.	Median	Mean	3rd Qt.	Max	Unit
ae1	7	218.2	340	295.1	363.5	450	FL
ae2	5	210.2	319	264.6	360	410	FL
se1	130	361	406.5	409.1	471.8	644	Kt
se2	144	354.8	421	397.9	487	589	Kt
dec1	0	0	189.5	310.5	368.2	3684	km
ded1	206	763.5	1437	1649.6	2204	10228	km
dcd1	78	507	1035	1343	1799	10029	km
dec2	0	60.25	155	297	364	3593	km
ded2	113	725	1092	1356	1890	4419	km
dcd2	99	375.2	843.5	1063.1	1566	3881	km

Table C.2.: A summary of general statistics on the bearings of the flight contextual information

Vars	0-45	45-90	90-135	135-180	180-225	225-270	270-315	315-360
bec1	29	48	16	15	133	76	58	23
bed1	42	67	33	31	18	101	79	27
bcd1	42	59	40	33	17	112	68	27
bec2	35	123	66	16	31	53	37	37
bed2	41	122	72	19	17	46	46	35
bcd2	35	108	85	25	14	49	42	40

C.2 Summary of Logistic Regression Model

C.2.1 Summary of Target Prediction Model

```
glm(formula = target ~ se2 + ae2 + dec1 + ded1 + se1 + ded2,
```

Table C.3.: A summary of general statistics on the aircraft operational phases from the flight contextual information

Vars	Ascending	After Ascending	Cruising	Before Descending	Descending
pe1	105	13	280	0	0
pc1	1	6	380	3	8
pe2	110	19	246	23	0
pc2	0	79	245	74	0

Table C.4.: A summary of general statistics on the operational phase shift between prediction and conflict points from the flight contextual information

Vars	No	Yes
ps1	274	124
ps2	224	174

Table C.5.: A summary of general statistics on the air traffic volume from the flight contextual information

Var	Low	Medium	High
trf	220	113	65

Table C.6.: A summary of general statistics on the number of aircraft conflicts from each airspace from the flight contextual information

Var	ZLA	ZOB	ZTL
spc	147	125	126

```
    family = binomial(link = "logit"), data = trainingData)

Coefficients:
(Intercept)          se2          ae2         dec1         ded1          se1
 -4.7463055    0.0185030   -0.0025105   -0.0017759   -0.0004010   -0.0023419
       ded2
  0.0002823

Degrees of Freedom: 203 Total (i.e. Null);  197 Residual
Null Deviance:     282.8
Residual Deviance: 155  AIC: 169
> summary(logitMod)

Call:
glm(formula = target ~ se2 + ae2 + dec1 + ded1 + se1 + ded2,
    family = binomial(link = "logit"), data = trainingData)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.65814  -0.44961   0.05003   0.63104   2.84757

Coefficients:
              Estimate Std. Error z value   Pr(>|z|)
(Intercept) -4.7463055  1.4373623  -3.302    0.00096 ***
se2          0.0185030  0.0036280   5.100 0.00000034 ***
ae2         -0.0025105  0.0031414  -0.799    0.42419
dec1        -0.0017759  0.0006406  -2.772    0.00557 **
ded1        -0.0004010  0.0001711  -2.343    0.01912 *
se1         -0.0023419  0.0022687  -1.032    0.30195
```

```
ded2         0.0002823  0.0002656   1.063    0.28789
---
Signif. codes:  0 ¡®***¡ 0.001 ¡®**¡ 0.01 ¡®*¡ 0.05 ¡®.¡ 0.1 ¡® ¡ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 282.80  on 203  degrees of freedom
Residual deviance: 155.01  on 197  degrees of freedom
AIC: 169.01

Number of Fisher Scoring iterations: 6
```

C.2.2 Summary of Type Prediction Model without Subset

```
nnet::multinom(formula = typ ~ se2 + ae2 + dec2 + dec1 + se1,
    data = trainingData)

Coefficients:
  (Intercept)           se2         ae2          dec2          dec1
2   -0.557113  0.0009246036 0.002673106 -0.0006225627 -5.703310e-05
3   -1.014638 -0.0009404605 0.001859659 -0.0001592554 -2.632669e-05
            se1
2 -0.0008044989
3  0.0023832509

Residual Deviance: 514.2216
AIC: 538.2216
```

C.2.3 Summary of Type Prediction Model with Subset

```
nnet::multinom(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 +
    bed2 + bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 +
    ae2 + se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2,
    data = trainingData)

Coefficients:
  (Intercept)        spc        bec1      bed1       bcd1      bec2     bed2
2   34.021747 -0.2901843 -0.83867403 -1.481402  2.7269205 -3.186156 3.279194
3   -5.017623 -0.2200366 -0.05811211  1.150842 -0.9477033 -3.369834 3.066768
        bcd2        pe1        pc1        pe2        pc2        ps1       ps2
2 0.01059772 -11.785016  0.9221981 -0.4115121  0.9084369 -24.338508 -0.375353
3 0.61859779   2.025582 -1.1315097  1.0673741 -0.9525173   2.993058  4.075416
         trf          ae1          ae2          se1          se2         dec1
2 -0.6919069 -0.009072344 -0.007713331 -0.006135893  0.014723464 -0.005336375
3 -0.6042728 -0.002681074  0.011590497 -0.002846873 -0.006526019 -0.010726208
        ded1         dcd1        dec2       ded2         dcd2
2 0.00381316 -0.004388568 -0.01053896 0.01049678 -0.009785021
3 0.01357881 -0.013258906 -0.01884138 0.01765899 -0.017198775

Residual Deviance: 145.9463
AIC: 245.9463

nnet::multinom(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 +
    bed2 + bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 +
    ae2 + se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2,
    data = trainingData)

Coefficients:
```

```
  (Intercept)         spc        bec1         bed1        bcd1       bec2       bed2
2   -27.98804 -0.1995953 -0.3922685  0.86700538 -0.3411799 0.4077495 0.02352039
3    -1.46358  0.4215342 -0.3900209 -0.05342395  0.5155255 0.3242543 0.31426653
        bcd2      pe1       pc1       pe2        pc2       ps1      ps2
2 -0.3537279 5.143271  3.437876 0.8747998 -0.7680122 10.836730 2.412887
3 -0.6805548 2.750653 -2.559945 1.9795706 -2.3605955  4.817403 1.737234
         trf          ae1          ae2          se1           se2        dec1
2 -0.3560385 -0.009403769 0.012072200 0.011582465 -0.004473685  0.01233706
3  0.7276730  0.001754004 0.006662273 0.003762165 -0.009167765 -0.19528398
         ded1         dcd1         dec2         ded2         dcd2
2 -0.01576582  0.01507883  0.12254944 -0.12756197  0.12710403
3  0.18062417 -0.17975186 -0.01375648  0.02644726 -0.02696998

Residual Deviance: 210.1437
AIC: 310.1437
```

C.2.4 Summary of Option Prediction Model without Subset

```
glm(formula = opt ~ dec1 + dcd1 + ded2, family = binomial(link = "logit"),
    data = trainingData)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9032  -1.0842  -0.1313   1.1359   1.7160

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.3885355  0.3074342  -1.264 0.206302
dec1         0.0015430  0.0004475   3.448 0.000564 ***
```

```
dcd1         0.0002602  0.0001377   1.890 0.058808 .
ded2        -0.0002976  0.0001721  -1.730 0.083678 .
---
Signif. codes:  0 ¡®***¡ 0.001 ¡®**¡ 0.01 ¡®*¡ 0.05 ¡®.¡ 0.1 ¡® ¡ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 310.53  on 223  degrees of freedom
Residual deviance: 292.93  on 220  degrees of freedom
AIC: 300.93

Number of Fisher Scoring iterations: 4
```

C.2.5 Summary of Lateral Option Prediction Model

```
glm(formula = opt ~ dec1 + dcd1 + ded2, family = binomial(link = "logit"),
    data = trainingData)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.95651  -0.97444  -0.01701   1.04461   2.15177

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.1163337  0.5530613  -0.210  0.83340
dec1         0.0022554  0.0007382   3.055  0.00225 **
dcd1         0.0001688  0.0002714   0.622  0.53395
ded2        -0.0006198  0.0003125  -1.983  0.04735 *
---
```

```
Signif. codes:  0 ¡®***¡ 0.001 ¡®**¡ 0.01 ¡®*¡ 0.05 ¡®.¡ 0.1 ¡® ¡ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 116.45  on 83  degrees of freedom
Residual deviance: 102.85  on 80  degrees of freedom
AIC: 110.85

Number of Fisher Scoring iterations: 4
```

C.2.6 Summary of Vertical Option Prediction Model

```
glm(formula = opt ~ se1 + ae1 + dec2 + ded1 + dec1 + dcd2, family = binomial(link
    data = trainingData, maxit = 100)

Deviance Residuals:
          Min             1Q         Median             3Q            Max
-0.0000132301  -0.0000000211   0.0000000000   0.0000000211   0.0000126537

Coefficients:
                  Estimate     Std. Error z value Pr(>|z|)
(Intercept)    3048.950915 5129122.399999   0.001        1
se1              -0.868209    3459.761321   0.000        1
ae1              -8.701267   14749.335192  -0.001        1
dec2              1.193501    2582.032040   0.000        1
ded1             -0.002253     201.558839   0.000        1
dec1             -0.562966    1431.148132   0.000        1
dcd2              0.013546     477.194391   0.000        1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 108.13096016735146  on 77  degrees of freedom
Residual deviance:   0.00000000049957  on 71  degrees of freedom
AIC: 14

Number of Fisher Scoring iterations: 31
```

C.2.7 Summary of Speed Option Prediction Model

```
glm(formula = opt ~ ae1 + se1 + ae2 + se2, family = binomial(link = "logit"),
    data = trainingData)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1491  -0.7920  -0.1351   0.5908   2.4977

Coefficients:
             Estimate Std. Error z value        Pr(>|z|)
(Intercept)  8.419496   1.260698   6.678 0.0000000000242 ***
ae1         -0.013278   0.002218  -5.986 0.0000000021520 ***
se1         -0.009484   0.002707  -3.503         0.00046 ***
ae2         -0.003639   0.002176  -1.672         0.09447 .
se2          0.001303   0.002322   0.561         0.57471
---
Signif. codes:  0 ¡®***¡ 0.001 ¡®**¡ 0.01 ¡®*¡ 0.05 ¡®.¡ 0.1 ¡® ¡ 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 440.84  on 317  degrees of freedom
Residual deviance: 300.10  on 313  degrees of freedom
AIC: 310.1

Number of Fisher Scoring iterations: 5
```

C.3 Summary of Regression Tree Model

C.3.1 Summary of Target Prediction Model

```
rpart(formula = target ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 204

          CP nsplit rel error    xerror        xstd
1 0.37977791      0 1.0000000 1.0069942 0.002656555
2 0.22195181      1 0.6202221 0.6689290 0.058960162
3 0.09667777      2 0.3982703 0.4458072 0.069108699
4 0.01339223      4 0.2049148 0.3861196 0.069551648
5 0.01000000      5 0.1915225 0.4234607 0.073241742

Variable importance
 se2  ae2  pe2 bec1 dec2 dec1  pc2  ps2 bed1 ded2 bcd1 dcd1 ded1  se1  ae1 dcd2
  16   15   12   11    9    7    7    6    5    3    3    2    2    1    1    1

Node number 1: 204 observations,    complexity param=0.3797779
  mean=0.5, MSE=0.25
  left son=2 (59 obs) right son=3 (145 obs)
```

```
  Primary splits:
      se2  < 332    to the left,  improve=0.3797779, (0 missing)
      ae2  < 147    to the left,  improve=0.3610216, (0 missing)
      dec1 < 41     to the right, improve=0.3161290, (0 missing)
      bec1 < 4.5    to the left,  improve=0.2616992, (0 missing)
      pe2  < 1.5    to the left,  improve=0.2323232, (0 missing)
  Surrogate splits:
      ae2  < 122    to the left,  agree=0.985, adj=0.949, (0 split)
      pe2  < 1.5    to the left,  agree=0.936, adj=0.780, (0 split)
      pc2  < 2.5    to the left,  agree=0.838, adj=0.441, (0 split)
      ps2  < 0.5    to the right, agree=0.819, adj=0.373, (0 split)
      dcd1 < 186    to the left,  agree=0.740, adj=0.102, (0 split)

Node number 2: 59 observations
  mean=0.01694915, MSE=0.01666188

Node number 3: 145 observations,    complexity param=0.2219518
  mean=0.6965517, MSE=0.2113674
  left son=6 (33 obs) right son=7 (112 obs)
  Primary splits:
      bec1 < 3.5    to the left,  improve=0.3693370, (0 missing)
      dec1 < 41     to the right, improve=0.2223597, (0 missing)
      dec2 < 74.5   to the right, improve=0.1665643, (0 missing)
      ded1 < 2547   to the right, improve=0.1428168, (0 missing)
      bcd2 < 3.5    to the right, improve=0.1364378, (0 missing)
  Surrogate splits:
      bed1 < 2.5    to the left,  agree=0.876, adj=0.455, (0 split)
      bcd1 < 3.5    to the left,  agree=0.841, adj=0.303, (0 split)
      dec1 < 947.5  to the right, agree=0.821, adj=0.212, (0 split)
```

```
    dec2 < 1038.5 to the right, agree=0.814, adj=0.182, (0 split)
    ded2 < 3955.5 to the right, agree=0.807, adj=0.152, (0 split)

Node number 6: 33 observations,    complexity param=0.01339223
  mean=0.1818182, MSE=0.1487603
  left son=12 (23 obs) right son=13 (10 obs)
  Primary splits:
    bec1 < 1.5    to the right, improve=0.13913040, (0 missing)
    bed1 < 1.5    to the right, improve=0.13913040, (0 missing)
    ded1 < 2453   to the right, improve=0.12698410, (0 missing)
    se1  < 416    to the right, improve=0.11111110, (0 missing)
    dcd1 < 1743   to the right, improve=0.09661836, (0 missing)
  Surrogate splits:
    bed1 < 1.5    to the right, agree=0.939, adj=0.8, (0 split)
    bcd1 < 1.5    to the right, agree=0.909, adj=0.7, (0 split)
    se1  < 391.5  to the right, agree=0.848, adj=0.5, (0 split)
    se2  < 361    to the right, agree=0.788, adj=0.3, (0 split)
    ae1  < 64     to the right, agree=0.758, adj=0.2, (0 split)

Node number 7: 112 observations,    complexity param=0.09667777
  mean=0.8482143, MSE=0.1287468
  left son=14 (63 obs) right son=15 (49 obs)
  Primary splits:
    dec1 < 41     to the right, improve=0.1391813, (0 missing)
    bed2 < 3.5    to the right, improve=0.1367686, (0 missing)
    bcd2 < 3.5    to the right, improve=0.1294668, (0 missing)
    se2  < 433    to the left,  improve=0.1198585, (0 missing)
    bec2 < 5.5    to the right, improve=0.1011315, (0 missing)
  Surrogate splits:
```

```
    dec2 < 78     to the right, agree=0.973, adj=0.939, (0 split)
    bec1 < 5.5    to the right, agree=0.902, adj=0.776, (0 split)
    ded1 < 904    to the right, agree=0.795, adj=0.531, (0 split)
    ae1  < 320.5  to the left,  agree=0.768, adj=0.469, (0 split)
    se1  < 461    to the left,  agree=0.741, adj=0.408, (0 split)

Node number 12: 23 observations
  mean=0.08695652, MSE=0.07939509

Node number 13: 10 observations
  mean=0.4, MSE=0.24

Node number 14: 63 observations,    complexity param=0.09667777
  mean=0.7301587, MSE=0.197027
  left son=28 (16 obs) right son=29 (47 obs)
  Primary splits:
    dec2 < 182    to the left,  improve=0.6327543, (0 missing)
    se2  < 433.5  to the left,  improve=0.2811267, (0 missing)
    dec1 < 188    to the left,  improve=0.2573496, (0 missing)
    bed2 < 3.5    to the right, improve=0.2546203, (0 missing)
    bcd2 < 3.5    to the right, improve=0.2307815, (0 missing)
  Surrogate splits:
    dec1 < 138.5  to the left,  agree=0.889, adj=0.562, (0 split)
    ded2 < 370    to the left,  agree=0.825, adj=0.312, (0 split)
    ded1 < 752.5  to the left,  agree=0.778, adj=0.125, (0 split)
    dcd1 < 2994.5 to the right, agree=0.778, adj=0.125, (0 split)
    dcd2 < 150.5  to the left,  agree=0.778, adj=0.125, (0 split)

Node number 15: 49 observations
```

```
  mean=1, MSE=0


Node number 28: 16 observations
  mean=0.125, MSE=0.109375


Node number 29: 47 observations
  mean=0.9361702, MSE=0.05975555
```

C.3.2 Summary of Type Prediction Model without Subset

```
rpart(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 240

           CP nsplit rel error   xerror       xstd
1  0.04155882      0 1.0000000 1.004642 0.04588912
2  0.04012911      1 0.9584412 1.019967 0.05347565
3  0.03152277      4 0.8380539 1.084923 0.06737887
4  0.02870001      5 0.8065311 1.110868 0.07963709
5  0.02541388      6 0.7778311 1.157586 0.08385732
6  0.02305093      8 0.7270033 1.179505 0.08967628
7  0.01968925     10 0.6809015 1.253160 0.09432882
8  0.01743862     12 0.6415230 1.295550 0.09881095
9  0.01508049     13 0.6240844 1.300536 0.09934985
10 0.01393353     14 0.6090039 1.315588 0.10097117
11 0.01256837     15 0.5950703 1.301660 0.10116419
12 0.01000000     16 0.5825020 1.295678 0.10119038
```

```
Variable importance
dec1 dec2 ded1  ae1  se1 dcd1  se2 bec1 dcd2  pe1 ded2  ps1 bec2 bed2 bcd2 bed1
  15   13   10   10    7    7    6    4    4    3    3    3    3    3    2    2
 ae2  ps2  pc2 bcd1  trf
   1    1    1    1    1

Node number 1: 240 observations,    complexity param=0.04155882
  mean=2, MSE=0.6666667
  left son=2 (57 obs) right son=3 (183 obs)
  Primary splits:
      se1  < 352.5  to the left,  improve=0.04155882, (0 missing)
      ae1  < 16     to the left,  improve=0.02909483, (0 missing)
      ae2  < 9.5    to the left,  improve=0.02909483, (0 missing)
      se2  < 161.5  to the left,  improve=0.02143708, (0 missing)
      ded1 < 305    to the right, improve=0.01973684, (0 missing)
  Surrogate splits:
      ae1 < 144.5  to the left,  agree=0.850, adj=0.368, (0 split)
      pe1 < 1.5    to the left,  agree=0.796, adj=0.140, (0 split)
      pc1 < 2.5    to the left,  agree=0.783, adj=0.088, (0 split)

Node number 2: 57 observations,    complexity param=0.01968925
  mean=1.701754, MSE=0.3847338
  left son=4 (11 obs) right son=5 (46 obs)
  Primary splits:
      ded1 < 716    to the left,  improve=0.11440470, (0 missing)
      dcd1 < 597    to the left,  improve=0.11440470, (0 missing)
      ae1  < 355    to the right, improve=0.11366630, (0 missing)
      dec1 < 386    to the right, improve=0.11206670, (0 missing)
```

```
      bec1 < 5.5    to the left,  improve=0.09984416, (0 missing)
  Surrogate splits:
      dcd1 < 597    to the left,  agree=0.930, adj=0.636, (0 split)
      dec1 < 13     to the left,  agree=0.877, adj=0.364, (0 split)
      dec2 < 44     to the left,  agree=0.877, adj=0.364, (0 split)
      ae1  < 345    to the right, agree=0.842, adj=0.182, (0 split)
      se1  < 347    to the right, agree=0.825, adj=0.091, (0 split)

Node number 3: 183 observations,    complexity param=0.04012911
  mean=2.092896, MSE=0.7181463
  left son=6 (10 obs) right son=7 (173 obs)
  Primary splits:
      se2  < 161.5  to the left,  improve=0.03864358, (0 missing)
      ae2  < 9.5    to the left,  improve=0.03608405, (0 missing)
      se1  < 433    to the right, improve=0.03484594, (0 missing)
      dec1 < 437.5  to the right, improve=0.02305329, (0 missing)
      ae1  < 337.5  to the left,  improve=0.02015689, (0 missing)
  Surrogate splits:
      ae2 < 6.5    to the left,  agree=0.951, adj=0.1, (0 split)

Node number 4: 11 observations
  mean=1.272727, MSE=0.1983471

Node number 5: 46 observations,    complexity param=0.01968925
  mean=1.804348, MSE=0.3747637
  left son=10 (9 obs) right son=11 (37 obs)
  Primary splits:
      dec1 < 386    to the right, improve=0.2199463, (0 missing)
      ae1  < 16     to the left,  improve=0.1726289, (0 missing)
```

```
      bec1 < 3.5    to the left,  improve=0.1211854, (0 missing)
      bed1 < 3.5    to the left,  improve=0.1211854, (0 missing)
      bcd1 < 3.5    to the left,  improve=0.1211854, (0 missing)
  Surrogate splits:
      dec2 < 404    to the right, agree=0.935, adj=0.667, (0 split)
      dcd1 < 614.5  to the left,  agree=0.870, adj=0.333, (0 split)
      ae1  < 11.5   to the left,  agree=0.848, adj=0.222, (0 split)
      se1  < 146    to the left,  agree=0.848, adj=0.222, (0 split)

Node number 6: 10 observations
  mean=1.4, MSE=0.44

Node number 7: 173 observations,    complexity param=0.04012911
  mean=2.132948, MSE=0.7048682
  left son=14 (72 obs) right son=15 (101 obs)
  Primary splits:
      se1  < 433    to the right, improve=0.03083646, (0 missing)
      se2  < 165.5  to the right, improve=0.02798661, (0 missing)
      ae1  < 337.5  to the left,  improve=0.02515373, (0 missing)
      dec1 < 163    to the left,  improve=0.02207765, (0 missing)
      ded1 < 2688   to the right, improve=0.01596646, (0 missing)
  Surrogate splits:
      bed1 < 4.5    to the left,  agree=0.757, adj=0.417, (0 split)
      bcd1 < 4.5    to the left,  agree=0.757, adj=0.417, (0 split)
      ae1  < 360.5  to the right, agree=0.699, adj=0.278, (0 split)
      bec1 < 4.5    to the left,  agree=0.676, adj=0.222, (0 split)
      dec2 < 87.5   to the left,  agree=0.630, adj=0.111, (0 split)

Node number 10: 9 observations
```

```
  mean=1.222222, MSE=0.1728395

Node number 11: 37 observations,    complexity param=0.01256837
  mean=1.945946, MSE=0.3214025
  left son=22 (30 obs) right son=23 (7 obs)
  Primary splits:
      dec1 < 303    to the left,  improve=0.16910170, (0 missing)
      dcd1 < 861    to the right, improve=0.14445290, (0 missing)
      dec2 < 330.5  to the left,  improve=0.08380952, (0 missing)
      se1  < 258.5  to the right, improve=0.08380952, (0 missing)
      se2  < 490.5  to the right, improve=0.07800325, (0 missing)
  Surrogate splits:
      dec2 < 354    to the left,  agree=0.919, adj=0.571, (0 split)
      se1  < 258.5  to the right, agree=0.838, adj=0.143, (0 split)

Node number 14: 72 observations,    complexity param=0.02541388
  mean=1.958333, MSE=0.7065972
  left son=28 (60 obs) right son=29 (12 obs)
  Primary splits:
      ded1 < 354.5  to the right, improve=0.05945946, (0 missing)
      se1  < 490.5  to the left,  improve=0.05010854, (0 missing)
      ae2  < 370.5  to the right, improve=0.04277344, (0 missing)
      bec2 < 7.5    to the right, improve=0.03716216, (0 missing)
      bcd1 < 1.5    to the left,  improve=0.03716216, (0 missing)
  Surrogate splits:
      dcd1 < 354.5  to the right, agree=0.958, adj=0.750, (0 split)
      dec2 < 3      to the right, agree=0.847, adj=0.083, (0 split)

Node number 15: 101 observations,    complexity param=0.04012911
```

```
  mean=2.257426, MSE=0.6664053
  left son=30 (55 obs) right son=31 (46 obs)
  Primary splits:
      ae1  < 335.5  to the left,  improve=0.15485980, (0 missing)
      ded2 < 1717.5 to the right, improve=0.08100208, (0 missing)
      dec2 < 763.5  to the right, improve=0.07074273, (0 missing)
      ded1 < 2260.5 to the right, improve=0.05815315, (0 missing)
      bec2 < 7.5    to the left,  improve=0.05767130, (0 missing)
  Surrogate splits:
      ps1  < 0.5    to the right, agree=0.762, adj=0.478, (0 split)
      pe1  < 2.5    to the left,  agree=0.743, adj=0.435, (0 split)
      dec1 < 115    to the right, agree=0.673, adj=0.283, (0 split)
      dec2 < 73     to the right, agree=0.653, adj=0.239, (0 split)
      se2  < 466    to the left,  agree=0.644, adj=0.217, (0 split)

Node number 22: 30 observations
  mean=1.833333, MSE=0.2055556

Node number 23: 7 observations
  mean=2.428571, MSE=0.5306122

Node number 28: 60 observations,    complexity param=0.02541388
  mean=1.866667, MSE=0.7488889
  left son=56 (32 obs) right son=57 (28 obs)
  Primary splits:
      ded1 < 1994   to the left,  improve=0.11366710, (0 missing)
      dec1 < 164.5  to the left,  improve=0.07869463, (0 missing)
      dcd1 < 1769.5 to the left,  improve=0.05775018, (0 missing)
      dec2 < 656    to the left,  improve=0.05568397, (0 missing)
```

```
    ded2 < 2036   to the left,  improve=0.04910887, (0 missing)
  Surrogate splits:
    dcd1 < 1686   to the left,  agree=0.883, adj=0.750, (0 split)
    bec1 < 2.5    to the right, agree=0.733, adj=0.429, (0 split)
    ded2 < 1013.5 to the left,  agree=0.733, adj=0.429, (0 split)
    dcd2 < 903    to the left,  agree=0.700, adj=0.357, (0 split)
    bed1 < 2.5    to the right, agree=0.683, adj=0.321, (0 split)

Node number 29: 12 observations
  mean=2.416667, MSE=0.2430556

Node number 30: 55 observations,    complexity param=0.02870001
  mean=1.963636, MSE=0.7259504
  left son=60 (12 obs) right son=61 (43 obs)
  Primary splits:
    dec1 < 625.5  to the right, improve=0.11500910, (0 missing)
    dec2 < 763.5  to the right, improve=0.10707210, (0 missing)
    se1  < 397.5  to the right, improve=0.10408530, (0 missing)
    ded1 < 2093   to the right, improve=0.09836066, (0 missing)
    se2  < 422    to the right, improve=0.09405175, (0 missing)
  Surrogate splits:
    dec2 < 482.5  to the right, agree=0.964, adj=0.833, (0 split)
    ae1  < 143.5  to the left,  agree=0.818, adj=0.167, (0 split)
    se2  < 536.5  to the right, agree=0.818, adj=0.167, (0 split)
    bec1 < 6.5    to the right, agree=0.800, adj=0.083, (0 split)

Node number 31: 46 observations,    complexity param=0.03152277
  mean=2.608696, MSE=0.36862
  left son=62 (24 obs) right son=63 (22 obs)
```

```
  Primary splits:
      dec1 < 150.5  to the left,  improve=0.2974456, (0 missing)
      ded1 < 664    to the left,  improve=0.2642660, (0 missing)
      dcd2 < 1086   to the right, improve=0.2566774, (0 missing)
      dec2 < 251.5  to the left,  improve=0.2009926, (0 missing)
      dcd1 < 468    to the left,  improve=0.1950000, (0 missing)
  Surrogate splits:
      dec2 < 115.5  to the left,  agree=0.891, adj=0.773, (0 split)
      bec1 < 5.5    to the left,  agree=0.783, adj=0.545, (0 split)
      ded1 < 854    to the left,  agree=0.761, adj=0.500, (0 split)
      dcd2 < 780    to the right, agree=0.717, adj=0.409, (0 split)
      ps2  < 0.5    to the left,  agree=0.696, adj=0.364, (0 split)

Node number 56: 32 observations,    complexity param=0.01743862
  mean=1.59375, MSE=0.6162109
  left son=112 (18 obs) right son=113 (14 obs)
  Primary splits:
      ded1 < 753    to the right, improve=0.14149880, (0 missing)
      ae1  < 385    to the left,  improve=0.08927628, (0 missing)
      ded2 < 920    to the right, improve=0.07066133, (0 missing)
      spc  < 1.5    to the right, improve=0.06918311, (0 missing)
      dec2 < 65     to the right, improve=0.06918311, (0 missing)
  Surrogate splits:
      dcd1 < 569.5  to the right, agree=0.906, adj=0.786, (0 split)
      trf  < 2.5    to the left,  agree=0.719, adj=0.357, (0 split)
      dec1 < 33.5   to the right, agree=0.688, adj=0.286, (0 split)
      dec2 < 38.5   to the right, agree=0.688, adj=0.286, (0 split)
      ded2 < 396.5  to the right, agree=0.656, adj=0.214, (0 split)
```

```
Node number 57: 28 observations,    complexity param=0.01393353
  mean=2.178571, MSE=0.7181122
  left son=114 (10 obs) right son=115 (18 obs)
  Primary splits:
      dec2 < 118    to the left,  improve=0.11087430, (0 missing)
      dcd1 < 2122   to the right, improve=0.10790410, (0 missing)
      dec1 < 189    to the left,  improve=0.10595910, (0 missing)
      ded2 < 1546   to the left,  improve=0.09663433, (0 missing)
      dcd2 < 1291   to the left,  improve=0.09663433, (0 missing)
  Surrogate splits:
      dec1 < 189    to the left,  agree=0.893, adj=0.7, (0 split)
      bec1 < 4      to the right, agree=0.786, adj=0.4, (0 split)
      ae2  < 280.5  to the left,  agree=0.786, adj=0.4, (0 split)
      pe2  < 3.5    to the right, agree=0.750, adj=0.3, (0 split)
      pc2  < 2.5    to the left,  agree=0.750, adj=0.3, (0 split)

Node number 60: 12 observations
  mean=1.416667, MSE=0.5763889

Node number 61: 43 observations,    complexity param=0.02305093
  mean=2.116279, MSE=0.6608978
  left son=122 (10 obs) right son=123 (33 obs)
  Primary splits:
      dec1 < 123.5  to the left,  improve=0.12221400, (0 missing)
      bec2 < 2.5    to the left,  improve=0.08274421, (0 missing)
      se1  < 398    to the right, improve=0.07897100, (0 missing)
      se2  < 424    to the right, improve=0.05219888, (0 missing)
      bed2 < 2.5    to the left,  improve=0.05050464, (0 missing)
  Surrogate splits:
```

```
      dec2 < 65.5   to the left,  agree=0.930, adj=0.7, (0 split)
      se2  < 475.5  to the right, agree=0.837, adj=0.3, (0 split)
      ded1 < 417    to the left,  agree=0.837, adj=0.3, (0 split)
      ae1  < 325    to the right, agree=0.814, adj=0.2, (0 split)
      dcd1 < 433    to the left,  agree=0.791, adj=0.1, (0 split)

Node number 62: 24 observations,    complexity param=0.01508049
  mean=2.291667, MSE=0.4565972
  left son=124 (13 obs) right son=125 (11 obs)
  Primary splits:
      ded2 < 1106   to the right, improve=0.2201867, (0 missing)
      dcd2 < 1086   to the right, improve=0.2201867, (0 missing)
      se2  < 485    to the right, improve=0.1330798, (0 missing)
      dec2 < 52.5   to the right, improve=0.1330798, (0 missing)
      dcd1 < 468    to the left,  improve=0.1117871, (0 missing)
  Surrogate splits:
      dcd2 < 1086   to the right, agree=1.000, adj=1.000, (0 split)
      pc2  < 3.5    to the left,  agree=0.750, adj=0.455, (0 split)
      spc  < 1.5    to the left,  agree=0.667, adj=0.273, (0 split)
      bec2 < 1.5    to the right, agree=0.667, adj=0.273, (0 split)
      bed2 < 1.5    to the right, agree=0.667, adj=0.273, (0 split)

Node number 63: 22 observations
  mean=2.954545, MSE=0.04338843

Node number 112: 18 observations
  mean=1.333333, MSE=0.5555556

Node number 113: 14 observations
```

```
  mean=1.928571, MSE=0.494898

Node number 114: 10 observations
  mean=1.8, MSE=0.76

Node number 115: 18 observations
  mean=2.388889, MSE=0.5709877

Node number 122: 10 observations
  mean=1.6, MSE=0.64

Node number 123: 33 observations,    complexity param=0.02305093
  mean=2.272727, MSE=0.5619835
  left son=246 (13 obs) right son=247 (20 obs)
  Primary splits:
      bec2 < 2.5    to the left,  improve=0.2104638, (0 missing)
      bed2 < 2.5    to the left,  improve=0.2104638, (0 missing)
      dec2 < 170.5  to the right, improve=0.1796218, (0 missing)
      bcd2 < 2.5    to the left,  improve=0.1289099, (0 missing)
      dec1 < 255    to the right, improve=0.1176471, (0 missing)
  Surrogate splits:
      bed2 < 2.5    to the left,  agree=1.000, adj=1.000, (0 split)
      bcd2 < 2.5    to the left,  agree=0.970, adj=0.923, (0 split)
      dec2 < 174.5  to the right, agree=0.727, adj=0.308, (0 split)
      se2  < 424    to the right, agree=0.697, adj=0.231, (0 split)
      ae2  < 337.5  to the right, agree=0.667, adj=0.154, (0 split)

Node number 124: 13 observations
  mean=2, MSE=0.4615385
```

```
Node number 125: 11 observations
  mean=2.636364, MSE=0.231405

Node number 246: 13 observations
  mean=1.846154, MSE=0.7455621

Node number 247: 20 observations
  mean=2.55, MSE=0.2475
```

C.3.3 Summary of Type Prediction Model with Subset

```
rpart(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 102

          CP nsplit rel error    xerror       xstd
1 0.15705128      0 1.0000000 1.0176750 0.07145909
2 0.07570539      1 0.8429487 0.9279692 0.09592258
3 0.05594546      2 0.7672433 1.0987037 0.12503291
4 0.02762148      5 0.5979799 1.2638739 0.14503979
5 0.02761438      6 0.5703584 1.2515210 0.14460224
6 0.01584323      7 0.5427441 1.2615990 0.14556892
7 0.01000000      8 0.5269008 1.2615990 0.14556892

Variable importance
bcd2 bed2 bec2 dcd1  ae1 bed1 dcd2 bec1 ded2  se1 bcd1  ae2  se2 ded1  pc1  pc2
```

```
  19   18   14    6    5    5    5    5    4    4    4    2    2    2    2    1
dec1 dec2
   1    1

Node number 1: 102 observations,    complexity param=0.1570513
  mean=2, MSE=0.6666667
  left son=2 (24 obs) right son=3 (78 obs)
  Primary splits:
      bcd2 < 2.5    to the left,  improve=0.15705130, (0 missing)
      bed2 < 2.5    to the left,  improve=0.10666670, (0 missing)
      ae1  < 373.5  to the right, improve=0.09590410, (0 missing)
      ded2 < 2054.5 to the left,  improve=0.05283434, (0 missing)
      dcd1 < 369    to the left,  improve=0.05000000, (0 missing)
  Surrogate splits:
      bed2 < 2.5    to the left,  agree=0.971, adj=0.875, (0 split)
      bec2 < 2.5    to the left,  agree=0.902, adj=0.583, (0 split)
      dcd2 < 160    to the left,  agree=0.794, adj=0.125, (0 split)
      ae1  < 378    to the right, agree=0.784, adj=0.083, (0 split)
      se2  < 444    to the right, agree=0.784, adj=0.083, (0 split)

Node number 2: 24 observations,    complexity param=0.02761438
  mean=1.416667, MSE=0.4097222
  left son=4 (15 obs) right son=5 (9 obs)
  Primary splits:
      dcd2 < 1291   to the left,  improve=0.1909605, (0 missing)
      bed2 < 1.5    to the left,  improve=0.1748184, (0 missing)
      bcd2 < 1.5    to the left,  improve=0.1748184, (0 missing)
      ae1  < 365.5  to the right, improve=0.1748184, (0 missing)
      ded2 < 992.5  to the left,  improve=0.1367232, (0 missing)
```

```
  Surrogate splits:
      ded2 < 1686.5 to the left,  agree=0.958, adj=0.889, (0 split)
      bed2 < 1.5    to the left,  agree=0.792, adj=0.444, (0 split)
      bcd2 < 1.5    to the left,  agree=0.792, adj=0.444, (0 split)
      ae2  < 16.5   to the right, agree=0.792, adj=0.444, (0 split)
      se2  < 176.5  to the right, agree=0.750, adj=0.333, (0 split)

Node number 3: 78 observations,    complexity param=0.07570539
  mean=2.179487, MSE=0.60881
  left son=6 (11 obs) right son=7 (67 obs)
  Primary splits:
      dcd1 < 369    to the left,  improve=0.10840750, (0 missing)
      ded1 < 2468.5 to the left,  improve=0.09296189, (0 missing)
      ded2 < 2054.5 to the left,  improve=0.08413311, (0 missing)
      bec2 < 4.5    to the right, improve=0.06533477, (0 missing)
      bed1 < 1.5    to the left,  improve=0.05553456, (0 missing)
  Surrogate splits:
      pc1  < 3.5    to the right, agree=0.910, adj=0.364, (0 split)
      ae2  < 9.5    to the left,  agree=0.897, adj=0.273, (0 split)
      ded1 < 438.5  to the left,  agree=0.897, adj=0.273, (0 split)

Node number 4: 15 observations
  mean=1.2, MSE=0.16

Node number 5: 9 observations
  mean=1.777778, MSE=0.617284

Node number 6: 11 observations
  mean=1.545455, MSE=0.6115702
```

```
Node number 7: 67 observations,    complexity param=0.05594546
  mean=2.283582, MSE=0.5315215
  left son=14 (44 obs) right son=15 (23 obs)
  Primary splits:
      bec2 < 4.5    to the right, improve=0.10395000, (0 missing)
      bed1 < 1.5    to the left,  improve=0.07468936, (0 missing)
      dec2 < 663.5  to the left,  improve=0.07130034, (0 missing)
      ded1 < 2468.5 to the left,  improve=0.07116435, (0 missing)
      dcd1 < 1579.5 to the left,  improve=0.06994329, (0 missing)
  Surrogate splits:
      bed2 < 4.5    to the right, agree=0.955, adj=0.870, (0 split)
      bcd2 < 4.5    to the right, agree=0.881, adj=0.652, (0 split)
      se2  < 418.5  to the left,  agree=0.716, adj=0.174, (0 split)
      dcd2 < 277    to the right, agree=0.701, adj=0.130, (0 split)
      pc2  < 3.5    to the left,  agree=0.687, adj=0.087, (0 split)

Node number 14: 44 observations,    complexity param=0.05594546
  mean=2.113636, MSE=0.6007231
  left son=28 (7 obs) right son=29 (37 obs)
  Primary splits:
      bed1 < 1.5    to the left,  improve=0.14780370, (0 missing)
      bcd2 < 5.5    to the left,  improve=0.13331970, (0 missing)
      bec2 < 5.5    to the left,  improve=0.09258774, (0 missing)
      bed2 < 5.5    to the left,  improve=0.08832521, (0 missing)
      bcd1 < 1.5    to the left,  improve=0.08551775, (0 missing)
  Surrogate splits:
      bec1 < 1.5    to the left,  agree=0.977, adj=0.857, (0 split)
      bcd1 < 1.5    to the left,  agree=0.955, adj=0.714, (0 split)
```

```
    ae1  < 43     to the left,  agree=0.886, adj=0.286, (0 split)
    se1  < 212.5  to the left,  agree=0.886, adj=0.286, (0 split)

Node number 15: 23 observations,    complexity param=0.02762148
  mean=2.608696, MSE=0.2381853
  left son=30 (15 obs) right son=31 (8 obs)
  Primary splits:
    se1  < 420    to the left,  improve=0.3428571, (0 missing)
    dec1 < 222.5  to the left,  improve=0.1916100, (0 missing)
    ded1 < 2458.5 to the left,  improve=0.1587963, (0 missing)
    bec1 < 2.5    to the right, improve=0.1587963, (0 missing)
    dcd1 < 2108.5 to the left,  improve=0.1133787, (0 missing)
  Surrogate splits:
    ded2 < 1065.5 to the left,  agree=0.870, adj=0.625, (0 split)
    ae1  < 335    to the left,  agree=0.826, adj=0.500, (0 split)
    dcd2 < 1566   to the left,  agree=0.826, adj=0.500, (0 split)
    dec1 < 423    to the left,  agree=0.783, adj=0.375, (0 split)
    ded1 < 2699   to the left,  agree=0.783, adj=0.375, (0 split)

Node number 28: 7 observations
  mean=1.428571, MSE=0.244898

Node number 29: 37 observations,    complexity param=0.05594546
  mean=2.243243, MSE=0.5624543
  left son=58 (8 obs) right son=59 (29 obs)
  Primary splits:
    bcd2 < 5.5    to the left,  improve=0.1874664, (0 missing)
    ae2  < 80     to the left,  improve=0.1164266, (0 missing)
    se2  < 259    to the left,  improve=0.1164266, (0 missing)
```

```
    ded2 < 892    to the left,  improve=0.1164266, (0 missing)
    bed2 < 5.5    to the left,  improve=0.1160730, (0 missing)
  Surrogate splits:
    bed2 < 5.5    to the left,  agree=0.973, adj=0.875, (0 split)
    bec2 < 5.5    to the left,  agree=0.946, adj=0.750, (0 split)
    ae1  < 373.5  to the right, agree=0.865, adj=0.375, (0 split)
    ded2 < 851    to the left,  agree=0.838, adj=0.250, (0 split)
    dec2 < 62     to the left,  agree=0.811, adj=0.125, (0 split)

Node number 30: 15 observations
  mean=2.4, MSE=0.24

Node number 31: 8 observations
  mean=3, MSE=0

Node number 58: 8 observations
  mean=1.625, MSE=0.484375

Node number 59: 29 observations,    complexity param=0.01584323
  mean=2.413793, MSE=0.4494649
  left son=118 (14 obs) right son=119 (15 obs)
  Primary splits:
    bec1 < 5.5    to the left,  improve=0.08265306, (0 missing)
    se1  < 452    to the right, improve=0.07316552, (0 missing)
    ae2  < 17.5   to the left,  improve=0.07068846, (0 missing)
    ded1 < 1678.5 to the right, improve=0.06735343, (0 missing)
    bed1 < 6.5    to the left,  improve=0.06402116, (0 missing)
  Surrogate splits:
    bed1 < 4.5    to the left,  agree=0.897, adj=0.786, (0 split)
```

```
    bcd1 < 4.5    to the left,  agree=0.862, adj=0.714, (0 split)
    se1  < 464    to the right, agree=0.828, adj=0.643, (0 split)
    pc2  < 2.5    to the right, agree=0.724, adj=0.429, (0 split)
    ae1  < 330    to the right, agree=0.724, adj=0.429, (0 split)

Node number 118: 14 observations
  mean=2.214286, MSE=0.4540816

Node number 119: 15 observations
  mean=2.6, MSE=0.3733333

rpart(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 138

          CP nsplit rel error   xerror       xstd
1 0.07618595      0 1.0000000 1.005925 0.06060532
2 0.04853053      4 0.6910782 1.135535 0.10059195
3 0.04809783      5 0.6425477 1.144058 0.10952217
4 0.02705882      7 0.5463520 1.127966 0.11992197
5 0.01369160      8 0.5192932 1.120199 0.12225021
6 0.01000000      9 0.5056016 1.125410 0.12396525

Variable importance
 se1  ae1 dec1 dcd1 dcd2 ded1 ded2  se2 bec1 dec2 bcd1 bed1  ae2  pc2  pe1 bcd2
  11   10    9    9    8    7    7    5    5    4    4    4    3    3    2    2
bec2 bed2  ps1  ps2  pe2
   2    2    2    1    1
```

```
Node number 1: 138 observations,    complexity param=0.07618595
  mean=2, MSE=0.6666667
  left son=2 (30 obs) right son=3 (108 obs)
  Primary splits:
      ded2 < 1844.5 to the right, improve=0.06666667, (0 missing)
      ae1  < 209.5  to the left,  improve=0.06233766, (0 missing)
      dec1 < 423    to the right, improve=0.06224385, (0 missing)
      pe1  < 1.5    to the left,  improve=0.05991678, (0 missing)
      dec2 < 365.5  to the right, improve=0.05991678, (0 missing)
  Surrogate splits:
      dcd2 < 1668.5 to the right, agree=0.920, adj=0.633, (0 split)
      dec1 < 1153   to the right, agree=0.804, adj=0.100, (0 split)
      dec2 < 1343   to the right, agree=0.804, adj=0.100, (0 split)
      pe2  < 1.5    to the left,  agree=0.790, adj=0.033, (0 split)
      ae2  < 156.5  to the left,  agree=0.790, adj=0.033, (0 split)

Node number 2: 30 observations,    complexity param=0.04809783
  mean=1.6, MSE=0.5733333
  left son=4 (8 obs) right son=5 (22 obs)
  Primary splits:
      dec1 < 384.5  to the right, improve=0.2283298, (0 missing)
      se2  < 466    to the left,  improve=0.1937984, (0 missing)
      dec2 < 605.5  to the right, improve=0.1911021, (0 missing)
      se1  < 470    to the left,  improve=0.1748150, (0 missing)
      spc  < 2.5    to the left,  improve=0.1564351, (0 missing)
  Surrogate splits:
      dec2 < 529    to the right, agree=0.967, adj=0.875, (0 split)
      dcd2 < 1362.5 to the left,  agree=0.867, adj=0.500, (0 split)
```

```
    bec1 < 5.5    to the right, agree=0.800, adj=0.250, (0 split)
    se2  < 572.5  to the right, agree=0.800, adj=0.250, (0 split)
    dcd1 < 282.5  to the left,  agree=0.800, adj=0.250, (0 split)

Node number 3: 108 observations,    complexity param=0.07618595
  mean=2.111111, MSE=0.6358025
  left son=6 (19 obs) right son=7 (89 obs)
  Primary splits:
    se1  < 337.5  to the left,  improve=0.11482840, (0 missing)
    ae1  < 335    to the left,  improve=0.08307039, (0 missing)
    pe1  < 1.5    to the left,  improve=0.07246696, (0 missing)
    dcd1 < 698.5  to the left,  improve=0.06908883, (0 missing)
    dec2 < 3      to the left,  improve=0.06817961, (0 missing)
  Surrogate splits:
    ae1 < 144.5  to the left,  agree=0.935, adj=0.632, (0 split)
    pe1 < 1.5    to the left,  agree=0.852, adj=0.158, (0 split)
    pc1 < 2.5    to the left,  agree=0.833, adj=0.053, (0 split)
    ps1 < 0.5    to the right, agree=0.833, adj=0.053, (0 split)

Node number 4: 8 observations
  mean=1, MSE=0

Node number 5: 22 observations,    complexity param=0.04809783
  mean=1.818182, MSE=0.6033058
  left son=10 (10 obs) right son=11 (12 obs)
  Primary splits:
    se2  < 462    to the left,  improve=0.37089040, (0 missing)
    dec1 < 179    to the left,  improve=0.17661450, (0 missing)
    dec2 < 235    to the left,  improve=0.17661450, (0 missing)
```

```
      ae1  < 325    to the right, improve=0.09846622, (0 missing)
      dcd2 < 2440.5 to the right, improve=0.09589041, (0 missing)
  Surrogate splits:
      ae2  < 217    to the left,  agree=0.773, adj=0.5, (0 split)
      bec2 < 5.5    to the right, agree=0.727, adj=0.4, (0 split)
      bed2 < 4.5    to the right, agree=0.727, adj=0.4, (0 split)
      bcd2 < 4.5    to the right, agree=0.727, adj=0.4, (0 split)
      bec1 < 4.5    to the left,  agree=0.682, adj=0.3, (0 split)

Node number 6: 19 observations
  mean=1.526316, MSE=0.3545706

Node number 7: 89 observations,    complexity param=0.07618595
  mean=2.235955, MSE=0.6072466
  left son=14 (34 obs) right son=15 (55 obs)
  Primary splits:
      ae1  < 335    to the left,  improve=0.08845920, (0 missing)
      bed1 < 1.5    to the left,  improve=0.08325288, (0 missing)
      bcd1 < 1.5    to the left,  improve=0.08325288, (0 missing)
      dcd1 < 698.5  to the left,  improve=0.07151351, (0 missing)
      ded1 < 699.5  to the left,  improve=0.05667738, (0 missing)
  Surrogate splits:
      pe1  < 1.5    to the left,  agree=0.742, adj=0.324, (0 split)
      ps1  < 0.5    to the right, agree=0.742, adj=0.324, (0 split)
      dec2 < 228.5  to the right, agree=0.708, adj=0.235, (0 split)
      dec1 < 140.5  to the right, agree=0.697, adj=0.206, (0 split)
      bec1 < 6.5    to the right, agree=0.674, adj=0.147, (0 split)

Node number 10: 10 observations
```

```
  mean=1.3, MSE=0.21

Node number 11: 12 observations
  mean=2.25, MSE=0.5208333

Node number 14: 34 observations,    complexity param=0.04853053
  mean=1.941176, MSE=0.6435986
  left son=28 (15 obs) right son=29 (19 obs)
  Primary splits:
      dcd2 < 644    to the left,  improve=0.2040370, (0 missing)
      dec2 < 57.5   to the right, improve=0.1362903, (0 missing)
      dec1 < 60.5   to the right, improve=0.1303356, (0 missing)
      spc  < 2.5    to the right, improve=0.1085248, (0 missing)
      bed1 < 1.5    to the left,  improve=0.1058486, (0 missing)
  Surrogate splits:
      pc2  < 3.5    to the right, agree=0.853, adj=0.667, (0 split)
      ded2 < 812.5  to the left,  agree=0.853, adj=0.667, (0 split)
      se1  < 400    to the left,  agree=0.765, adj=0.467, (0 split)
      bec1 < 5.5    to the right, agree=0.735, adj=0.400, (0 split)
      dec1 < 60.5   to the right, agree=0.735, adj=0.400, (0 split)

Node number 15: 55 observations,    complexity param=0.07618595
  mean=2.418182, MSE=0.4978512
  left son=30 (25 obs) right son=31 (30 obs)
  Primary splits:
      dcd1 < 698.5  to the left,  improve=0.3513944, (0 missing)
      ded1 < 660.5  to the left,  improve=0.3288361, (0 missing)
      se1  < 503    to the right, improve=0.1705770, (0 missing)
      dec1 < 161.5  to the left,  improve=0.1584881, (0 missing)
```

```
      ae2  < 357    to the left,  improve=0.1263574, (0 missing)
  Surrogate splits:
      ded1 < 660.5  to the left,  agree=0.982, adj=0.96, (0 split)
      dec1 < 148.5  to the left,  agree=0.709, adj=0.36, (0 split)
      bed1 < 4.5    to the left,  agree=0.691, adj=0.32, (0 split)
      bcd1 < 4.5    to the left,  agree=0.691, adj=0.32, (0 split)
      se1  < 419.5  to the right, agree=0.673, adj=0.28, (0 split)

Node number 28: 15 observations
  mean=1.533333, MSE=0.3822222

Node number 29: 19 observations
  mean=2.263158, MSE=0.6149584

Node number 30: 25 observations,    complexity param=0.02705882
  mean=1.96, MSE=0.4384
  left son=60 (8 obs) right son=61 (17 obs)
  Primary splits:
      ae1  < 354.5  to the left,  improve=0.22713610, (0 missing)
      ded1 < 423    to the right, improve=0.13393580, (0 missing)
      dcd1 < 423    to the right, improve=0.13393580, (0 missing)
      bec2 < 4.5    to the right, improve=0.09707081, (0 missing)
      dec2 < 38.5   to the left,  improve=0.09707081, (0 missing)
  Surrogate splits:
      ps2 < 0.5    to the right, agree=0.84, adj=0.500, (0 split)
      ae2 < 269    to the left,  agree=0.84, adj=0.500, (0 split)
      pe2 < 2.5    to the left,  agree=0.80, adj=0.375, (0 split)
      pc2 < 2.5    to the left,  agree=0.76, adj=0.250, (0 split)
      se1 < 363.5  to the left,  agree=0.76, adj=0.250, (0 split)
```

```
Node number 31: 30 observations,    complexity param=0.0136916
  mean=2.8, MSE=0.2266667
  left son=62 (7 obs) right son=63 (23 obs)
  Primary splits:
      bed1 < 4.5    to the left,  improve=0.18523930, (0 missing)
      bcd1 < 4.5    to the left,  improve=0.18523930, (0 missing)
      dcd2 < 427.5  to the left,  improve=0.17647060, (0 missing)
      ded2 < 586.5  to the left,  improve=0.16549390, (0 missing)
      bec2 < 5.5    to the left,  improve=0.07563025, (0 missing)
  Surrogate splits:
      bcd1 < 4.5    to the left,  agree=1.000, adj=1.000, (0 split)
      se1  < 482    to the right, agree=0.933, adj=0.714, (0 split)
      bec1 < 4.5    to the left,  agree=0.900, adj=0.571, (0 split)
      ae1  < 405    to the right, agree=0.867, adj=0.429, (0 split)
      ae2  < 266    to the left,  agree=0.833, adj=0.286, (0 split)

Node number 60: 8 observations
  mean=1.5, MSE=0.25

Node number 61: 17 observations
  mean=2.176471, MSE=0.3806228

Node number 62: 7 observations
  mean=2.428571, MSE=0.5306122

Node number 63: 23 observations
  mean=2.913043, MSE=0.07939509
```

C.3.4 Summary of Option Prediction Model without Subset

```
rpart(formula = opt ~ bec1 + bed1 + bcd1 + bec2 + bed2 + bcd2 +
    pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 + se1 +
    se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 224

          CP nsplit rel error    xerror       xstd
1 0.33395176      0 1.0000000 1.0106677 0.00310672
2 0.10674434      1 0.6660482 0.7054137 0.05720985
3 0.05181834      2 0.5593039 0.6356760 0.05942800
4 0.02918470      4 0.4556672 0.6039539 0.06755229
5 0.02150974      6 0.3972978 0.6692541 0.07454612
6 0.01508621      8 0.3542783 0.7156079 0.08117682
7 0.01000000      9 0.3391921 0.7549787 0.08421693

Variable importance
 ae1  pe1  ps1 dec2 dec1  se1 ded1  ae2  pe2 dcd1 ded2  se2 bec1  pc2  pc1  trf
  18   17   15   12   10    9    3    3    2    2    2    2    2    1    1    1
 ps2
   1

Node number 1: 224 observations,    complexity param=0.3339518
  mean=0.5, MSE=0.25
  left son=2 (154 obs) right son=3 (70 obs)
  Primary splits:
      pe1  < 1.5    to the right, improve=0.3339518, (0 missing)
      ae1  < 254.5  to the right, improve=0.3339518, (0 missing)
```

```
    ps1  < 0.5    to the left,  improve=0.3038848, (0 missing)
    dec1 < 13     to the left,  improve=0.2808475, (0 missing)
    dec2 < 71.5   to the left,  improve=0.1765942, (0 missing)
  Surrogate splits:
    ae1  < 254.5  to the right, agree=1.000, adj=1.000, (0 split)
    ps1  < 0.5    to the left,  agree=0.951, adj=0.843, (0 split)
    se1  < 358.5  to the right, agree=0.839, adj=0.486, (0 split)
    pc1  < 2.5    to the right, agree=0.701, adj=0.043, (0 split)
    dcd1 < 3503.5 to the left,  agree=0.701, adj=0.043, (0 split)

Node number 2: 154 observations,    complexity param=0.1067443
  mean=0.3051948, MSE=0.2120509
  left son=4 (58 obs) right son=5 (96 obs)
  Primary splits:
    dec1 < 33.5   to the left,  improve=0.18305090, (0 missing)
    dec2 < 78.5   to the left,  improve=0.11596550, (0 missing)
    ae2  < 111.5  to the right, improve=0.09915843, (0 missing)
    se2  < 334    to the right, improve=0.08595168, (0 missing)
    bec1 < 4.5    to the right, improve=0.07994492, (0 missing)
  Surrogate splits:
    dec2 < 78.5   to the left,  agree=0.948, adj=0.862, (0 split)
    ded1 < 783    to the left,  agree=0.773, adj=0.397, (0 split)
    ded2 < 333    to the left,  agree=0.714, adj=0.241, (0 split)
    pe2  < 3.5    to the right, agree=0.701, adj=0.207, (0 split)
    bec1 < 5.5    to the left,  agree=0.682, adj=0.155, (0 split)

Node number 3: 70 observations
  mean=0.9285714, MSE=0.06632653
```

```
Node number 4: 58 observations,    complexity param=0.01508621
  mean=0.05172414, MSE=0.04904875
  left son=8 (49 obs) right son=9 (9 obs)
  Primary splits:
      dec2 < 3      to the right, improve=0.29696970, (0 missing)
      bec2 < 4.5    to the left,  improve=0.11196170, (0 missing)
      ded1 < 325    to the right, improve=0.09338384, (0 missing)
      dcd1 < 325    to the right, improve=0.09338384, (0 missing)
      bed1 < 2.5    to the right, improve=0.04170274, (0 missing)
  Surrogate splits:
      bed1 < 1.5    to the right, agree=0.862, adj=0.111, (0 split)
      bcd1 < 1.5    to the right, agree=0.862, adj=0.111, (0 split)

Node number 5: 96 observations,    complexity param=0.05181834
  mean=0.4583333, MSE=0.2482639
  left son=10 (79 obs) right son=11 (17 obs)
  Primary splits:
      dec2 < 114    to the right, improve=0.11560070, (0 missing)
      dec1 < 314.5  to the left,  improve=0.05697207, (0 missing)
      se2  < 410.5  to the right, improve=0.04370629, (0 missing)
      ae2  < 311.5  to the right, improve=0.04370629, (0 missing)
      se1  < 432.5  to the left,  improve=0.04370629, (0 missing)
  Surrogate splits:
      pc2  < 2.5    to the right, agree=0.854, adj=0.176, (0 split)
      dec1 < 111.5  to the right, agree=0.854, adj=0.176, (0 split)
      se2  < 153.5  to the right, agree=0.844, adj=0.118, (0 split)
      ded1 < 373.5  to the right, agree=0.844, adj=0.118, (0 split)

Node number 8: 49 observations
```

```
  mean=0, MSE=0

Node number 9: 9 observations
  mean=0.3333333, MSE=0.2222222

Node number 10: 79 observations,    complexity param=0.05181834
  mean=0.3797468, MSE=0.2355392
  left son=20 (44 obs) right son=21 (35 obs)
  Primary splits:
      dec1 < 314.5  to the left,  improve=0.16383120, (0 missing)
      dec2 < 238.5  to the left,  improve=0.11931920, (0 missing)
      ae1  < 330.5  to the right, improve=0.07678623, (0 missing)
      se1  < 518.5  to the right, improve=0.05952381, (0 missing)
      trf  < 1.5    to the right, improve=0.04777647, (0 missing)
  Surrogate splits:
      dec2 < 352    to the left,  agree=0.886, adj=0.743, (0 split)
      se1  < 432.5  to the left,  agree=0.671, adj=0.257, (0 split)
      dcd1 < 881    to the right, agree=0.658, adj=0.229, (0 split)
      bec1 < 2.5    to the right, agree=0.646, adj=0.200, (0 split)
      ded1 < 1524.5 to the left,  agree=0.646, adj=0.200, (0 split)

Node number 11: 17 observations
  mean=0.8235294, MSE=0.1453287

Node number 20: 44 observations,    complexity param=0.02150974
  mean=0.2045455, MSE=0.1627066
  left son=40 (24 obs) right son=41 (20 obs)
  Primary splits:
      trf  < 1.5    to the right, improve=0.10835980, (0 missing)
```

```
      ps2  < 0.5    to the right, improve=0.07086168, (0 missing)
      se1  < 399.5  to the right, improve=0.07057387, (0 missing)
      ded1 < 1365.5 to the right, improve=0.06704788, (0 missing)
      dcd1 < 1022.5 to the right, improve=0.06678760, (0 missing)
  Surrogate splits:
      bec1 < 2.5    to the right, agree=0.727, adj=0.40, (0 split)
      ded1 < 1534   to the left,  agree=0.727, adj=0.40, (0 split)
      se1  < 403.5  to the left,  agree=0.705, adj=0.35, (0 split)
      dcd1 < 1320   to the left,  agree=0.705, adj=0.35, (0 split)
      bed1 < 2.5    to the right, agree=0.659, adj=0.25, (0 split)

Node number 21: 35 observations,    complexity param=0.0291847
  mean=0.6, MSE=0.24
  left son=42 (24 obs) right son=43 (11 obs)
  Primary splits:
      ae1  < 335    to the right, improve=0.18244950, (0 missing)
      bed1 < 6.5    to the right, improve=0.10289120, (0 missing)
      se1  < 502    to the right, improve=0.10289120, (0 missing)
      dcd2 < 1614   to the left,  improve=0.09336420, (0 missing)
      ae2  < 311.5  to the right, improve=0.09265351, (0 missing)
  Surrogate splits:
      pe1  < 2.5    to the right, agree=0.743, adj=0.182, (0 split)
      ps1  < 0.5    to the left,  agree=0.743, adj=0.182, (0 split)
      ae2  < 365    to the left,  agree=0.743, adj=0.182, (0 split)
      dec1 < 338    to the right, agree=0.743, adj=0.182, (0 split)
      dcd1 < 1379.5 to the left,  agree=0.743, adj=0.182, (0 split)

Node number 40: 24 observations
  mean=0.08333333, MSE=0.07638889
```

```
Node number 41: 20 observations,    complexity param=0.02150974
  mean=0.35, MSE=0.2275
  left son=82 (8 obs) right son=83 (12 obs)
  Primary splits:
      dec2 < 188    to the left,  improve=0.3589744, (0 missing)
      ded1 < 1365.5 to the right, improve=0.3140925, (0 missing)
      dcd1 < 1098.5 to the right, improve=0.3140925, (0 missing)
      dec1 < 174    to the left,  improve=0.1483516, (0 missing)
      se1  < 413    to the right, improve=0.1160488, (0 missing)
  Surrogate splits:
      pe2  < 2      to the left,  agree=0.8, adj=0.5, (0 split)
      pc2  < 2.5    to the left,  agree=0.8, adj=0.5, (0 split)
      ae2  < 196.5  to the left,  agree=0.8, adj=0.5, (0 split)
      se2  < 335    to the left,  agree=0.8, adj=0.5, (0 split)
      dec1 < 174    to the left,  agree=0.8, adj=0.5, (0 split)

Node number 42: 24 observations,    complexity param=0.0291847
  mean=0.4583333, MSE=0.2482639
  left son=84 (9 obs) right son=85 (15 obs)
  Primary splits:
      ae2  < 311.5  to the right, improve=0.29137530, (0 missing)
      dcd2 < 1400.5 to the left,  improve=0.16803200, (0 missing)
      dcd1 < 551.5  to the right, improve=0.10865600, (0 missing)
      se1  < 490    to the right, improve=0.08741259, (0 missing)
      bcd1 < 2.5    to the left,  improve=0.08741259, (0 missing)
  Surrogate splits:
      se2  < 454    to the right, agree=0.792, adj=0.444, (0 split)
      dec2 < 1363   to the right, agree=0.792, adj=0.444, (0 split)
```

```
      ps2  < 0.5    to the left,  agree=0.750, adj=0.333, (0 split)
      dec1 < 435.5  to the left,  agree=0.750, adj=0.333, (0 split)
      ded2 < 2566.5 to the right, agree=0.750, adj=0.333, (0 split)

Node number 43: 11 observations
  mean=0.9090909, MSE=0.08264463

Node number 82: 8 observations
  mean=0, MSE=0

Node number 83: 12 observations
  mean=0.5833333, MSE=0.2430556

Node number 84: 9 observations
  mean=0.1111111, MSE=0.09876543

Node number 85: 15 observations
  mean=0.6666667, MSE=0.2222222
```

C.3.5 Summary of Lateral Option Prediction Model

```
rpart(formula = opt ~ bec1 + bed1 + bcd1 + bec2 + bed2 + bcd2 +
    pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 + se1 +
    se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "anova")
  n= 84

          CP nsplit rel error    xerror        xstd
1 0.17006803      0 1.0000000 1.0185481 0.006495749
```

```
2 0.10554525      1 0.8299320 0.9401698 0.091379744
3 0.07265512      3 0.6188415 1.0222844 0.110558553
4 0.04081633      5 0.4735312 1.2327961 0.138121246
5 0.03463203      6 0.4327149 1.2175562 0.145941023
6 0.01000000      7 0.3980829 1.1702995 0.145333776

Variable importance
dec1 dec2 ded1 dcd1 ded2  se2 bec1 dcd2  se1 bcd1 bed1  pe2  ae2  pc2 bcd2 bec2
  19   17   10    8    7    6    5    5    5    4    4    2    2    2    1    1
bed2
   1

Node number 1: 84 observations,    complexity param=0.170068
  mean=0.5, MSE=0.25
  left son=2 (21 obs) right son=3 (63 obs)
  Primary splits:
      dec1 < 13     to the left,  improve=0.17006800, (0 missing)
      bec1 < 3.5    to the right, improve=0.09145881, (0 missing)
      dcd2 < 1956.5 to the right, improve=0.08775731, (0 missing)
      ded1 < 796    to the left,  improve=0.07331378, (0 missing)
      ded2 < 1239   to the right, improve=0.06863301, (0 missing)
  Surrogate splits:
      dec2 < 82.5   to the left,  agree=0.929, adj=0.714, (0 split)
      ded1 < 545.5  to the left,  agree=0.845, adj=0.381, (0 split)
      ded2 < 334.5  to the left,  agree=0.786, adj=0.143, (0 split)
      pe2  < 3.5    to the right, agree=0.774, adj=0.095, (0 split)
      se1  < 534    to the right, agree=0.762, adj=0.048, (0 split)

Node number 2: 21 observations,    complexity param=0.04081633
```

```
  mean=0.1428571, MSE=0.122449
  left son=4 (14 obs) right son=5 (7 obs)
  Primary splits:
      dec2 < 21.5   to the right, improve=0.3333333, (0 missing)
      se1  < 404.5  to the right, improve=0.2222222, (0 missing)
      bec2 < 4      to the left,  improve=0.2222222, (0 missing)
      ded2 < 1226   to the right, improve=0.1833333, (0 missing)
      dcd2 < 1211.5 to the right, improve=0.1833333, (0 missing)
  Surrogate splits:
      se1  < 427.5  to the right, agree=0.810, adj=0.429, (0 split)
      ded1 < 309.5  to the right, agree=0.810, adj=0.429, (0 split)
      dcd1 < 309.5  to the right, agree=0.810, adj=0.429, (0 split)
      se2  < 555.5  to the left,  agree=0.762, adj=0.286, (0 split)
      ae2  < 310    to the left,  agree=0.714, adj=0.143, (0 split)

Node number 3: 63 observations,    complexity param=0.1055452
  mean=0.6190476, MSE=0.2358277
  left son=6 (30 obs) right son=7 (33 obs)
  Primary splits:
      ded2 < 1394   to the right, improve=0.08951049, (0 missing)
      dec2 < 87     to the right, improve=0.07692308, (0 missing)
      dcd2 < 943    to the right, improve=0.07392452, (0 missing)
      se1  < 446    to the left,  improve=0.06552479, (0 missing)
      bec1 < 5.5    to the right, improve=0.05817308, (0 missing)
  Surrogate splits:
      dcd2 < 910    to the right, agree=0.905, adj=0.800, (0 split)
      dec2 < 570    to the right, agree=0.651, adj=0.267, (0 split)
      bed2 < 1.5    to the right, agree=0.619, adj=0.200, (0 split)
      bcd2 < 1.5    to the right, agree=0.603, adj=0.167, (0 split)
```

```
      pc2  < 3.5    to the left,  agree=0.603, adj=0.167, (0 split)

Node number 4: 14 observations
  mean=0, MSE=0

Node number 5: 7 observations
  mean=0.4285714, MSE=0.244898

Node number 6: 30 observations,    complexity param=0.1055452
  mean=0.4666667, MSE=0.2488889
  left son=12 (22 obs) right son=13 (8 obs)
  Primary splits:
      dec1 < 744    to the left,  improve=0.41558440, (0 missing)
      ded2 < 1826.5 to the left,  improve=0.12821650, (0 missing)
      dcd1 < 1261   to the right, improve=0.12574400, (0 missing)
      dec2 < 815    to the left,  improve=0.11728900, (0 missing)
      se2  < 175    to the right, improve=0.07497782, (0 missing)
  Surrogate splits:
      dec2 < 718    to the left,  agree=0.867, adj=0.500, (0 split)
      se2  < 158    to the right, agree=0.800, adj=0.250, (0 split)
      dcd2 < 593.5  to the right, agree=0.800, adj=0.250, (0 split)
      dcd1 < 314    to the right, agree=0.767, adj=0.125, (0 split)

Node number 7: 33 observations,    complexity param=0.07265512
  mean=0.7575758, MSE=0.1836547
  left son=14 (21 obs) right son=15 (12 obs)
  Primary splits:
      dcd1 < 1505   to the left,  improve=0.1828571, (0 missing)
      bec1 < 3.5    to the right, improve=0.1600000, (0 missing)
```

```
    ae2  < 58     to the left,  improve=0.1570652, (0 missing)
    se2  < 238    to the left,  improve=0.1570652, (0 missing)
    dec2 < 228.5  to the right, improve=0.1401667, (0 missing)
  Surrogate splits:
    ded1 < 1804   to the left,  agree=0.939, adj=0.833, (0 split)
    ded2 < 1143   to the left,  agree=0.818, adj=0.500, (0 split)
    se2  < 481    to the left,  agree=0.788, adj=0.417, (0 split)
    bcd2 < 3.5    to the right, agree=0.727, adj=0.250, (0 split)
    dec2 < 710    to the left,  agree=0.727, adj=0.250, (0 split)

Node number 12: 22 observations,    complexity param=0.03463203
  mean=0.2727273, MSE=0.1983471
  left son=24 (11 obs) right son=25 (11 obs)
  Primary splits:
    se2  < 404.5  to the right, improve=0.16666670, (0 missing)
    ae2  < 196    to the right, improve=0.10292020, (0 missing)
    dec2 < 373.5  to the right, improve=0.09116809, (0 missing)
    bec1 < 5.5    to the right, improve=0.06805556, (0 missing)
    dcd1 < 1109.5 to the right, improve=0.06805556, (0 missing)
  Surrogate splits:
    ae2  < 196    to the right, agree=0.909, adj=0.818, (0 split)
    bec2 < 2.5    to the left,  agree=0.818, adj=0.636, (0 split)
    pe2  < 1.5    to the right, agree=0.818, adj=0.636, (0 split)
    dec2 < 324.5  to the right, agree=0.818, adj=0.636, (0 split)
    pc2  < 2.5    to the right, agree=0.773, adj=0.545, (0 split)

Node number 13: 8 observations
  mean=1, MSE=0
```

```
Node number 14: 21 observations,    complexity param=0.07265512
  mean=0.6190476, MSE=0.2358277
  left son=28 (10 obs) right son=29 (11 obs)
  Primary splits:
      bec1 < 5.5    to the right, improve=0.3923951, (0 missing)
      dec2 < 228.5  to the right, improve=0.3042832, (0 missing)
      ded2 < 806    to the right, improve=0.2596154, (0 missing)
      ae2  < 93.5   to the left,  improve=0.2355769, (0 missing)
      se2  < 260    to the left,  improve=0.2355769, (0 missing)
  Surrogate splits:
      bed1 < 4.5    to the right, agree=0.857, adj=0.7, (0 split)
      bcd1 < 4.5    to the right, agree=0.857, adj=0.7, (0 split)
      se1  < 446    to the left,  agree=0.810, adj=0.6, (0 split)
      ded1 < 1203.5 to the right, agree=0.762, adj=0.5, (0 split)
      dcd1 < 1127.5 to the right, agree=0.762, adj=0.5, (0 split)

Node number 15: 12 observations
  mean=1, MSE=0

Node number 24: 11 observations
  mean=0.09090909, MSE=0.08264463

Node number 25: 11 observations
  mean=0.4545455, MSE=0.2479339

Node number 28: 10 observations
  mean=0.3, MSE=0.21

Node number 29: 11 observations
```

```
  mean=0.9090909, MSE=0.08264463
```

C.3.6 Summary of Vertical Option Prediction Model

```
rpart(formula = opt ~ bec1 + bed1 + bcd1 + bec2 + bed2 + bcd2 +
    pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 + se1 +
    se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2 + spc, data = trainingData,
    method = "anova")
  n= 78

          CP nsplit rel error    xerror        xstd
1 0.81395349      0 1.0000000 1.0222440 0.007317902
2 0.04827687      1 0.1860465 0.2367631 0.093979009
3 0.01000000      2 0.1377696 0.3005483 0.110972607

Variable importance
 ae1  pe1  ps1 dec1  se1 dec2  ae2  se2
  21   20   19   14   13   12    1    1

Node number 1: 78 observations,    complexity param=0.8139535
  mean=0.5, MSE=0.25
  left son=2 (43 obs) right son=3 (35 obs)
  Primary splits:
      ae1  < 319.5 to the right, improve=0.8139535, (0 missing)
      pe1  < 2.5   to the right, improve=0.7333333, (0 missing)
      ps1  < 0.5   to the left,  improve=0.6844920, (0 missing)
      dec1 < 158.5 to the left,  improve=0.5185185, (0 missing)
      se1  < 418.5 to the right, improve=0.4592391, (0 missing)
  Surrogate splits:
```

```
    pe1  < 2.5   to the right, agree=0.974, adj=0.943, (0 split)
    ps1  < 0.5   to the left,  agree=0.962, adj=0.914, (0 split)
    se1  < 383   to the right, agree=0.833, adj=0.629, (0 split)
    dec1 < 158.5 to the left,  agree=0.833, adj=0.629, (0 split)
    dec2 < 124   to the left,  agree=0.795, adj=0.543, (0 split)

Node number 2: 43 observations,    complexity param=0.04827687
  mean=0.09302326, MSE=0.08436993
  left son=4 (36 obs) right son=5 (7 obs)
  Primary splits:
    dec1 < 204   to the left,  improve=0.2594882, (0 missing)
    ded1 < 1688  to the left,  improve=0.1538656, (0 missing)
    dec2 < 150.5 to the left,  improve=0.1315742, (0 missing)
    se1  < 415   to the right, improve=0.1130583, (0 missing)
    dcd1 < 780.5 to the left,  improve=0.1074481, (0 missing)
  Surrogate splits:
    dec2 < 235   to the left,  agree=0.953, adj=0.714, (0 split)
    ae2  < 22.5  to the right, agree=0.907, adj=0.429, (0 split)
    se2  < 163.5 to the right, agree=0.907, adj=0.429, (0 split)
    bec1 < 2.5   to the right, agree=0.860, adj=0.143, (0 split)

Node number 3: 35 observations
  mean=1, MSE=0

Node number 4: 36 observations
  mean=0.02777778, MSE=0.02700617

Node number 5: 7 observations
  mean=0.4285714, MSE=0.244898
```

C.3.7 Summary of Speed Option Prediction Model

```
rpart(formula = opt ~ bec1 + bed1 + bcd1 + bec2 + bed2 + bcd2 +
    pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 + se1 +
    se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2 + spc, data = trainingData,
    method = "anova")
  n= 318

          CP nsplit rel error    xerror        xstd
1 0.37664649      0 1.0000000 1.0080322 0.002276636
2 0.06766184      1 0.6233535 0.6499659 0.049191009
3 0.04859884      2 0.5556917 0.6009185 0.046080804
4 0.02473875      3 0.5070928 0.5746115 0.050048277
5 0.01886792      8 0.3833991 0.6681436 0.061906689
6 0.01771443      9 0.3645312 0.6777525 0.064300565
7 0.01229962     10 0.3468167 0.6804925 0.066175753
8 0.01145327     11 0.3345171 0.6679592 0.066284612
9 0.01000000     12 0.3230638 0.6715594 0.066356560

Variable importance
 ae1  pe1  ps1  se1 dec1 dec2 ded2  pc1  ae2  se2 ded1 dcd2  pe2 dcd1  ps2 bec2
  21   20   13   11    7    5    4    3    3    3    2    2    1    1    1    1

Node number 1: 318 observations,    complexity param=0.3766465
  mean=0.5, MSE=0.25
  left son=2 (212 obs) right son=3 (106 obs)
  Primary splits:
      ae1  < 248.5  to the right, improve=0.3766465, (0 missing)
      pe1  < 1.5    to the right, improve=0.3667892, (0 missing)
```

```
      ps1  < 0.5    to the left,  improve=0.2678287, (0 missing)
      dec1 < 6.5    to the left,  improve=0.1954887, (0 missing)
      se1  < 388.5  to the right, improve=0.1850600, (0 missing)
  Surrogate splits:
      pe1 < 1.5    to the right, agree=0.997, adj=0.991, (0 split)
      ps1 < 0.5    to the left,  agree=0.884, adj=0.651, (0 split)
      se1 < 360    to the right, agree=0.805, adj=0.415, (0 split)
      pc1 < 2.5    to the right, agree=0.717, adj=0.151, (0 split)
      se2 < 157.5  to the right, agree=0.679, adj=0.038, (0 split)

Node number 2: 212 observations,    complexity param=0.06766184
  mean=0.2830189, MSE=0.2029192
  left son=4 (51 obs) right son=5 (161 obs)
  Primary splits:
      dec1 < 7      to the left,  improve=0.12504090, (0 missing)
      dec2 < 206.5  to the left,  improve=0.10076100, (0 missing)
      se1  < 342    to the right, improve=0.05546672, (0 missing)
      bec1 < 7.5    to the left,  improve=0.05157895, (0 missing)
      ae2  < 313    to the right, improve=0.03112795, (0 missing)
  Surrogate splits:
      dec2 < 64     to the left,  agree=0.958, adj=0.824, (0 split)
      ded1 < 364    to the left,  agree=0.788, adj=0.118, (0 split)
      ded2 < 289    to the left,  agree=0.788, adj=0.118, (0 split)
      pe2  < 3.5    to the right, agree=0.774, adj=0.059, (0 split)
      pc1  < 2.5    to the left,  agree=0.764, adj=0.020, (0 split)

Node number 3: 106 observations,    complexity param=0.01771443
  mean=0.9339623, MSE=0.06167675
  left son=6 (9 obs) right son=7 (97 obs)
```

```
  Primary splits:
      dcd2 < 181.5  to the left,  improve=0.2154105, (0 missing)
      bcd1 < 7.5    to the right, improve=0.2154105, (0 missing)
      bed1 < 7.5    to the right, improve=0.1883658, (0 missing)
      ae1  < 216    to the right, improve=0.1611059, (0 missing)
      ded2 < 432    to the left,  improve=0.1323515, (0 missing)
  Surrogate splits:
      ded2 < 314    to the left,  agree=0.934, adj=0.222, (0 split)

Node number 4: 51 observations
  mean=0, MSE=0

Node number 5: 161 observations,    complexity param=0.04859884
  mean=0.3726708, MSE=0.2337873
  left son=10 (144 obs) right son=11 (17 obs)
  Primary splits:
      se1  < 371.5  to the right, improve=0.10264700, (0 missing)
      ae2  < 333.5  to the right, improve=0.03724882, (0 missing)
      dcd1 < 667    to the right, improve=0.03703133, (0 missing)
      dec2 < 71.5   to the right, improve=0.03184333, (0 missing)
      bec1 < 7.5    to the left,  improve=0.03135454, (0 missing)
  Surrogate splits:
      se2  < 563.5  to the left,  agree=0.901, adj=0.059, (0 split)
      dec1 < 31     to the right, agree=0.901, adj=0.059, (0 split)
      dec2 < 44     to the right, agree=0.901, adj=0.059, (0 split)

Node number 6: 9 observations
  mean=0.5555556, MSE=0.2469136
```

```
Node number 7: 97 observations
  mean=0.9690722, MSE=0.0299713

Node number 10: 144 observations,    complexity param=0.02473875
  mean=0.3194444, MSE=0.2173997
  left son=20 (38 obs) right son=21 (106 obs)
  Primary splits:
      ae2  < 352.5  to the right, improve=0.05819864, (0 missing)
      dcd1 < 667    to the right, improve=0.04720036, (0 missing)
      bed1 < 5.5    to the right, improve=0.03354398, (0 missing)
      bcd1 < 5.5    to the right, improve=0.03354398, (0 missing)
      se1  < 515.5  to the right, improve=0.03207360, (0 missing)
  Surrogate splits:
      se2  < 483.5  to the right, agree=0.757, adj=0.079, (0 split)
      dec2 < 1840   to the right, agree=0.757, adj=0.079, (0 split)
      dcd2 < 184.5  to the left,  agree=0.757, adj=0.079, (0 split)
      se1  < 610.5  to the right, agree=0.750, adj=0.053, (0 split)
      dec1 < 1191.5 to the right, agree=0.750, adj=0.053, (0 split)

Node number 11: 17 observations
  mean=0.8235294, MSE=0.1453287

Node number 20: 38 observations,    complexity param=0.01229962
  mean=0.1315789, MSE=0.1142659
  left son=40 (28 obs) right son=41 (10 obs)
  Primary splits:
      ae1  < 375    to the left,  improve=0.22519480, (0 missing)
      dcd1 < 534.5  to the right, improve=0.08865801, (0 missing)
      ded1 < 812    to the right, improve=0.08865801, (0 missing)
```

```
    se2  < 490.5  to the right, improve=0.07878788, (0 missing)
    ae2  < 373.5  to the left,  improve=0.07103357, (0 missing)
  Surrogate splits:
    bec2 < 4      to the left,  agree=0.816, adj=0.3, (0 split)
    bed2 < 3.5    to the left,  agree=0.816, adj=0.3, (0 split)
    bcd2 < 3.5    to the left,  agree=0.789, adj=0.2, (0 split)
    ae2  < 365    to the right, agree=0.763, adj=0.1, (0 split)
    se2  < 413.5  to the right, agree=0.763, adj=0.1, (0 split)

Node number 21: 106 observations,    complexity param=0.02473875
  mean=0.3867925, MSE=0.2371841
  left son=42 (22 obs) right son=43 (84 obs)
  Primary splits:
    dcd2 < 2054   to the right, improve=0.06925107, (0 missing)
    se1  < 515.5  to the right, improve=0.06380851, (0 missing)
    dec2 < 206.5  to the left,  improve=0.06117719, (0 missing)
    ded2 < 2709.5 to the right, improve=0.05833744, (0 missing)
    dec1 < 1059   to the left,  improve=0.04308318, (0 missing)
  Surrogate splits:
    ded2 < 2510   to the right, agree=0.953, adj=0.773, (0 split)
    dcd1 < 2674   to the right, agree=0.849, adj=0.273, (0 split)
    ded1 < 3476   to the right, agree=0.840, adj=0.227, (0 split)
    se2  < 538    to the right, agree=0.802, adj=0.045, (0 split)

Node number 40: 28 observations
  mean=0.03571429, MSE=0.03443878

Node number 41: 10 observations
  mean=0.4, MSE=0.24
```

```
Node number 42: 22 observations
  mean=0.1363636, MSE=0.1177686

Node number 43: 84 observations,    complexity param=0.02473875
  mean=0.452381, MSE=0.2477324
  left son=86 (75 obs) right son=87 (9 obs)
  Primary splits:
      ded2 < 2136   to the left,  improve=0.09229596, (0 missing)
      se1  < 515.5  to the right, improve=0.06773455, (0 missing)
      dec2 < 549.5  to the left,  improve=0.06581911, (0 missing)
      ae1  < 336.5  to the right, improve=0.06581911, (0 missing)
      ae2  < 265    to the left,  improve=0.04735142, (0 missing)
  Surrogate splits:
      dec1 < 1108.5 to the left,  agree=0.940, adj=0.444, (0 split)
      dec2 < 969.5  to the left,  agree=0.917, adj=0.222, (0 split)

Node number 86: 75 observations,    complexity param=0.02473875
  mean=0.4, MSE=0.24
  left son=172 (36 obs) right son=173 (39 obs)
  Primary splits:
      ae2  < 265    to the left,  improve=0.08653846, (0 missing)
      pe2  < 1.5    to the left,  improve=0.07716049, (0 missing)
      se2  < 331.5  to the left,  improve=0.07407407, (0 missing)
      ded1 < 1083.5 to the right, improve=0.06463832, (0 missing)
      dec2 < 89     to the right, improve=0.06094527, (0 missing)
  Surrogate splits:
      pe2  < 1.5    to the left,  agree=0.920, adj=0.833, (0 split)
      se2  < 331.5  to the left,  agree=0.880, adj=0.750, (0 split)
```

```
    ps2  < 0.5    to the right, agree=0.827, adj=0.639, (0 split)
    pc2  < 2.5    to the left,  agree=0.733, adj=0.444, (0 split)
    ded2 < 1524.5 to the right, agree=0.693, adj=0.361, (0 split)

Node number 87: 9 observations
  mean=0.8888889, MSE=0.09876543

Node number 172: 36 observations,    complexity param=0.01145327
  mean=0.25, MSE=0.1875
  left son=344 (23 obs) right son=345 (13 obs)
  Primary splits:
    dec1 < 250    to the right, improve=0.1348941, (0 missing)
    se1  < 393.5  to the right, improve=0.1330049, (0 missing)
    dec2 < 91.5   to the right, improve=0.1330049, (0 missing)
    ae1  < 355    to the right, improve=0.1248710, (0 missing)
    trf  < 1.5    to the left,  improve=0.1082251, (0 missing)
  Surrogate splits:
    se1  < 382    to the right, agree=0.778, adj=0.385, (0 split)
    ded1 < 653    to the right, agree=0.750, adj=0.308, (0 split)
    dec2 < 78.5   to the right, agree=0.750, adj=0.308, (0 split)
    ae2  < 142.5  to the left,  agree=0.722, adj=0.231, (0 split)
    se2  < 189    to the left,  agree=0.722, adj=0.231, (0 split)

Node number 173: 39 observations,    complexity param=0.02473875
  mean=0.5384615, MSE=0.2485207
  left son=346 (15 obs) right son=347 (24 obs)
  Primary splits:
    dec1 < 220.5  to the left,  improve=0.2880952, (0 missing)
    dcd1 < 688    to the right, improve=0.2102096, (0 missing)
```

```
      dec2 < 270.5  to the left,  improve=0.1975309, (0 missing)
      ae2  < 315    to the right, improve=0.1591546, (0 missing)
      ded1 < 1215   to the right, improve=0.1504386, (0 missing)
  Surrogate splits:
      dec2 < 246.5  to the left,  agree=0.872, adj=0.667, (0 split)
      se2  < 408    to the left,  agree=0.744, adj=0.333, (0 split)
      ded2 < 795    to the left,  agree=0.744, adj=0.333, (0 split)
      ae2  < 315    to the right, agree=0.718, adj=0.267, (0 split)
      ded1 < 462    to the left,  agree=0.692, adj=0.200, (0 split)

Node number 344: 23 observations
  mean=0.1304348, MSE=0.1134216

Node number 345: 13 observations
  mean=0.4615385, MSE=0.2485207

Node number 346: 15 observations
  mean=0.2, MSE=0.16

Node number 347: 24 observations,    complexity param=0.01886792
  mean=0.75, MSE=0.1875
  left son=694 (12 obs) right son=695 (12 obs)
  Primary splits:
      ded1 < 1225.5 to the right, improve=0.3333333, (0 missing)
      bec1 < 2.5    to the left,  improve=0.2987654, (0 missing)
      bed1 < 2.5    to the left,  improve=0.2987654, (0 missing)
      dcd1 < 688    to the right, improve=0.2820513, (0 missing)
      bcd1 < 2.5    to the left,  improve=0.2268908, (0 missing)
  Surrogate splits:
```

```
    dcd1 < 688    to the right, agree=0.875, adj=0.750, (0 split)
    dec1 < 460    to the right, agree=0.750, adj=0.500, (0 split)
    ded2 < 1130   to the right, agree=0.750, adj=0.500, (0 split)
    bec1 < 2.5    to the left,  agree=0.708, adj=0.417, (0 split)
    bec2 < 6.5    to the left,  agree=0.708, adj=0.417, (0 split)

Node number 694: 12 observations
  mean=0.5, MSE=0.25

Node number 695: 12 observations
  mean=1, MSE=0
```

C.4 Summary of Classification Tree Model

C.4.1 Summary of Target Prediction Model

```
rpart(formula = target ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "class")
  n= 204

          CP nsplit rel error    xerror       xstd
1 0.55882353      0 1.0000000 1.1764706 0.06891520
2 0.20588235      1 0.4411765 0.4509804 0.05851837
3 0.05882353      2 0.2352941 0.2450980 0.04591782
4 0.01000000      4 0.1176471 0.2058824 0.04255200

Variable importance
 se2  ae2  pe2 bec1 dec2 dec1  pc2  ps2 bed1 ded2 bcd1 dcd1 ded1 dcd2  ae1  se1
```

```
  16   15   12   11   10    7    7    6    4    3    3    2    2    1    1    1

Node number 1: 204 observations,    complexity param=0.5588235
  predicted class=0  expected loss=0.5  P(node) =1
    class counts:   102   102
   probabilities: 0.500 0.500
  left son=2 (59 obs) right son=3 (145 obs)
  Primary splits:
      se2  < 332    to the left,  improve=38.73735, (0 missing)
      ae2  < 147    to the left,  improve=36.82420, (0 missing)
      dec1 < 41     to the right, improve=32.24516, (0 missing)
      bec1 < 4.5    to the left,  improve=26.69332, (0 missing)
      pe2  < 1.5    to the left,  improve=23.69697, (0 missing)
  Surrogate splits:
      ae2  < 122    to the left,  agree=0.985, adj=0.949, (0 split)
      pe2  < 1.5    to the left,  agree=0.936, adj=0.780, (0 split)
      pc2  < 2.5    to the left,  agree=0.838, adj=0.441, (0 split)
      ps2  < 0.5    to the right, agree=0.819, adj=0.373, (0 split)
      dcd1 < 186    to the left,  agree=0.740, adj=0.102, (0 split)

Node number 2: 59 observations
  predicted class=0  expected loss=0.01694915  P(node) =0.2892157
    class counts:    58     1
   probabilities: 0.983 0.017

Node number 3: 145 observations,    complexity param=0.2058824
  predicted class=1  expected loss=0.3034483  P(node) =0.7107843
    class counts:    44   101
   probabilities: 0.303 0.697
```

```
  left son=6 (33 obs) right son=7 (112 obs)
  Primary splits:
      bec1 < 3.5    to the left,  improve=22.639080, (0 missing)
      dec1 < 41     to the right, improve=13.629890, (0 missing)
      dec2 < 74.5   to the right, improve=10.209820, (0 missing)
      ded1 < 2547   to the right, improve= 8.754179, (0 missing)
      bcd2 < 3.5    to the right, improve= 8.363166, (0 missing)
  Surrogate splits:
      bed1 < 2.5    to the left,  agree=0.876, adj=0.455, (0 split)
      bcd1 < 3.5    to the left,  agree=0.841, adj=0.303, (0 split)
      dec1 < 947.5  to the right, agree=0.821, adj=0.212, (0 split)
      dec2 < 1038.5 to the right, agree=0.814, adj=0.182, (0 split)
      ded2 < 3955.5 to the right, agree=0.807, adj=0.152, (0 split)

Node number 6: 33 observations
  predicted class=0  expected loss=0.1818182  P(node) =0.1617647
    class counts:    27     6
   probabilities: 0.818 0.182

Node number 7: 112 observations,    complexity param=0.05882353
  predicted class=1  expected loss=0.1517857  P(node) =0.5490196
    class counts:    17    95
   probabilities: 0.152 0.848
  left son=14 (63 obs) right son=15 (49 obs)
  Primary splits:
      dec1 < 41     to the right, improve=4.013889, (0 missing)
      bed2 < 3.5    to the right, improve=3.944309, (0 missing)
      bcd2 < 3.5    to the right, improve=3.733730, (0 missing)
      se2  < 433    to the left,  improve=3.456634, (0 missing)
```

```
      bec2 < 5.5    to the right, improve=2.916560, (0 missing)
  Surrogate splits:
      dec2 < 78     to the right, agree=0.973, adj=0.939, (0 split)
      bec1 < 5.5    to the right, agree=0.902, adj=0.776, (0 split)
      ded1 < 904    to the right, agree=0.795, adj=0.531, (0 split)
      ae1  < 320.5  to the left,  agree=0.768, adj=0.469, (0 split)
      se1  < 461    to the left,  agree=0.741, adj=0.408, (0 split)

Node number 14: 63 observations,    complexity param=0.05882353
  predicted class=1  expected loss=0.2698413  P(node) =0.3088235
    class counts:    17    46
   probabilities: 0.270 0.730
  left son=28 (16 obs) right son=29 (47 obs)
  Primary splits:
      dec2 < 182    to the left,  improve=15.708380, (0 missing)
      se2  < 433.5  to the left,  improve= 6.979081, (0 missing)
      dec1 < 188    to the left,  improve= 6.388806, (0 missing)
      bed2 < 3.5    to the right, improve= 6.321049, (0 missing)
      bcd2 < 3.5    to the right, improve= 5.729243, (0 missing)
  Surrogate splits:
      dec1 < 138.5  to the left,  agree=0.889, adj=0.562, (0 split)
      ded2 < 370    to the left,  agree=0.825, adj=0.312, (0 split)
      ded1 < 752.5  to the left,  agree=0.778, adj=0.125, (0 split)
      dcd1 < 2994.5 to the right, agree=0.778, adj=0.125, (0 split)
      dcd2 < 150.5  to the left,  agree=0.778, adj=0.125, (0 split)

Node number 15: 49 observations
  predicted class=1  expected loss=0  P(node) =0.2401961
    class counts:     0    49
```

```
   probabilities: 0.000 1.000

Node number 28: 16 observations
  predicted class=0  expected loss=0.125  P(node) =0.07843137
    class counts:    14     2
   probabilities: 0.875 0.125

Node number 29: 47 observations
  predicted class=1  expected loss=0.06382979  P(node) =0.2303922
    class counts:     3    44
   probabilities: 0.064 0.936
```

C.4.2 Summary of Type Prediction Model without Subset

```
rpart(formula = typ ~ spc + bec1 + bed1 + bcd1 + bec2 + bed2 +
    bcd2 + pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 +
    se1 + se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "class")
  n= 240

        CP nsplit rel error  xerror       xstd
1 0.175000      0   1.00000 1.15625 0.04069505
2 0.050000      1   0.82500 0.88125 0.04766521
3 0.043750      3   0.72500 0.94375 0.04676898
4 0.028125      5   0.63750 0.88125 0.04766521
5 0.025000      7   0.58125 0.90625 0.04735002
6 0.015625     10   0.50625 0.86875 0.04780161
7 0.010000     12   0.47500 0.85000 0.04798003
```

```
Variable importance
dec2 dec1  se1  ae1  ae2  se2 bec1  pe1 bed1 bcd1  pe2 ded2 dcd1 ded1  ps1  pc2
  13   13    9    9    8    6    6    4    4    4    4    3    3    3    2    2
 ps2 dcd2 bec2 bed2  pc1 bcd2
   2    2    2    1    1    1

Node number 1: 240 observations,    complexity param=0.175
  predicted class=1  expected loss=0.6666667  P(node) =1
    class counts:    80    80    80
   probabilities: 0.333 0.333 0.333
  left son=2 (65 obs) right son=3 (175 obs)
  Primary splits:
      se1  < 358.5 to the left,  improve=8.327033, (0 missing)
      dec1 < 312.5 to the right, improve=6.312854, (0 missing)
      ae1  < 237   to the left,  improve=4.922451, (0 missing)
      pe1  < 1.5   to the left,  improve=4.450420, (0 missing)
      dec2 < 402.5 to the right, improve=4.014337, (0 missing)
  Surrogate splits:
      ae1 < 149.5 to the left,  agree=0.838, adj=0.400, (0 split)
      pe1 < 1.5   to the left,  agree=0.812, adj=0.308, (0 split)
      ps1 < 0.5   to the right, agree=0.767, adj=0.138, (0 split)
      pc1 < 2.5   to the left,  agree=0.750, adj=0.077, (0 split)

Node number 2: 65 observations,    complexity param=0.04375
  predicted class=2  expected loss=0.4615385  P(node) =0.2708333
    class counts:    23    35     7
   probabilities: 0.354 0.538 0.108
  left son=4 (17 obs) right son=5 (48 obs)
  Primary splits:
```

```
    dec1 < 314.5 to the right, improve=4.656146, (0 missing)
    bed1 < 3.5   to the left,  improve=4.352733, (0 missing)
    bcd1 < 3.5   to the left,  improve=4.352733, (0 missing)
    dec2 < 402.5 to the right, improve=3.525689, (0 missing)
    ded1 < 703   to the left,  improve=2.934939, (0 missing)
  Surrogate splits:
    dec2 < 402.5 to the right, agree=0.923, adj=0.706, (0 split)
    ae1  < 72.5  to the left,  agree=0.831, adj=0.353, (0 split)
    se1  < 251.5 to the left,  agree=0.831, adj=0.353, (0 split)
    bec1 < 2.5   to the left,  agree=0.769, adj=0.118, (0 split)
    bcd2 < 7.5   to the right, agree=0.754, adj=0.059, (0 split)

Node number 3: 175 observations,    complexity param=0.05
  predicted class=3  expected loss=0.5828571  P(node) =0.7291667
    class counts:    57    45    73
   probabilities: 0.326 0.257 0.417
  left son=6 (52 obs) right son=7 (123 obs)
  Primary splits:
    ae2  < 224.5 to the left,  improve=5.716307, (0 missing)
    dec1 < 156   to the left,  improve=4.763583, (0 missing)
    ps2  < 0.5   to the right, improve=4.475902, (0 missing)
    pe2  < 1.5   to the left,  improve=4.405368, (0 missing)
    se1  < 529.5 to the right, improve=3.727558, (0 missing)
  Surrogate splits:
    pe2 < 1.5   to the left,  agree=0.983, adj=0.942, (0 split)
    se2 < 327   to the left,  agree=0.943, adj=0.808, (0 split)
    pc2 < 2.5   to the left,  agree=0.869, adj=0.558, (0 split)
    ps2 < 0.5   to the right, agree=0.840, adj=0.462, (0 split)
    pc1 < 4.5   to the right, agree=0.726, adj=0.077, (0 split)
```

```
Node number 4: 17 observations
  predicted class=1  expected loss=0.4117647  P(node) =0.07083333
    class counts:    10     3     4
   probabilities: 0.588 0.176 0.235

Node number 5: 48 observations,    complexity param=0.025
  predicted class=2  expected loss=0.3333333  P(node) =0.2
    class counts:    13    32     3
   probabilities: 0.271 0.667 0.062
  left son=10 (11 obs) right son=11 (37 obs)
  Primary splits:
      dec1 < 67    to the left,  improve=4.132781, (0 missing)
      ded1 < 724   to the left,  improve=4.132781, (0 missing)
      dec2 < 70.5  to the left,  improve=4.132781, (0 missing)
      ae1  < 355   to the right, improve=3.949786, (0 missing)
      ps1  < 0.5   to the left,  improve=3.248714, (0 missing)
  Surrogate splits:
      dec2 < 70.5  to the left,  agree=1.000, adj=1.000, (0 split)
      ded1 < 724   to the left,  agree=0.875, adj=0.455, (0 split)
      ae1  < 345   to the right, agree=0.854, adj=0.364, (0 split)
      dcd1 < 384.5 to the left,  agree=0.833, adj=0.273, (0 split)
      bec1 < 5.5   to the left,  agree=0.812, adj=0.182, (0 split)

Node number 6: 52 observations,    complexity param=0.04375
  predicted class=1  expected loss=0.4807692  P(node) =0.2166667
    class counts:    27     3    22
   probabilities: 0.519 0.058 0.423
  left son=12 (39 obs) right son=13 (13 obs)
```

```
  Primary splits:
      ded2 < 950.5 to the right, improve=3.576923, (0 missing)
      se1  < 396.5 to the right, improve=2.894678, (0 missing)
      bed1 < 2.5   to the left,  improve=2.513889, (0 missing)
      bcd2 < 4.5   to the right, improve=2.245098, (0 missing)
      dcd2 < 752   to the right, improve=2.089744, (0 missing)
  Surrogate splits:
      dcd2 < 864   to the right, agree=0.846, adj=0.385, (0 split)
      dec2 < 82.5  to the right, agree=0.827, adj=0.308, (0 split)
      bed2 < 0.5   to the right, agree=0.788, adj=0.154, (0 split)
      bcd2 < 0.5   to the right, agree=0.788, adj=0.154, (0 split)
      dec1 < 33.5  to the right, agree=0.769, adj=0.077, (0 split)

Node number 7: 123 observations,    complexity param=0.05
  predicted class=3  expected loss=0.5853659  P(node) =0.5125
    class counts:    30    42    51
   probabilities: 0.244 0.341 0.415
  left son=14 (63 obs) right son=15 (60 obs)
  Primary splits:
      dec1 < 160   to the left,  improve=4.055439, (0 missing)
      dcd2 < 780   to the right, improve=3.629905, (0 missing)
      ded1 < 581   to the right, improve=2.976291, (0 missing)
      bed1 < 5.5   to the left,  improve=2.758120, (0 missing)
      bcd1 < 5.5   to the left,  improve=2.758120, (0 missing)
  Surrogate splits:
      dec2 < 128.5 to the left,  agree=0.943, adj=0.883, (0 split)
      ded1 < 763   to the left,  agree=0.797, adj=0.583, (0 split)
      dcd1 < 569.5 to the left,  agree=0.732, adj=0.450, (0 split)
      bec1 < 4     to the right, agree=0.699, adj=0.383, (0 split)
```

```
    pe1  < 2.5   to the right, agree=0.699, adj=0.383, (0 split)

Node number 10: 11 observations
  predicted class=1  expected loss=0.3636364  P(node) =0.04583333
    class counts:     7     3     1
   probabilities: 0.636 0.273 0.091

Node number 11: 37 observations
  predicted class=2  expected loss=0.2162162  P(node) =0.1541667
    class counts:     6    29     2
   probabilities: 0.162 0.784 0.054

Node number 12: 39 observations,    complexity param=0.015625
  predicted class=1  expected loss=0.3846154  P(node) =0.1625
    class counts:    24     3    12
   probabilities: 0.615 0.077 0.308
  left son=24 (12 obs) right son=25 (27 obs)
  Primary splits:
      se2  < 255   to the right, improve=2.548433, (0 missing)
      dec2 < 95.5  to the left,  improve=2.501241, (0 missing)
      se1  < 396.5 to the right, improve=2.380273, (0 missing)
      ae1  < 365.5 to the right, improve=2.132368, (0 missing)
      ae2  < 62    to the right, improve=2.132368, (0 missing)
  Surrogate splits:
      ae2  < 38    to the right, agree=0.974, adj=0.917, (0 split)
      dec1 < 164.5 to the left,  agree=0.897, adj=0.667, (0 split)
      dec2 < 80.5  to the left,  agree=0.821, adj=0.417, (0 split)
      bec2 < 7.5   to the right, agree=0.718, adj=0.083, (0 split)
      bed2 < 6.5   to the right, agree=0.718, adj=0.083, (0 split)
```

```
Node number 13: 13 observations
  predicted class=3  expected loss=0.2307692  P(node) =0.05416667
    class counts:     3     0    10
   probabilities: 0.231 0.000 0.769

Node number 14: 63 observations,    complexity param=0.028125
  predicted class=2  expected loss=0.5238095  P(node) =0.2625
    class counts:    14    30    19
   probabilities: 0.222 0.476 0.302
  left son=28 (32 obs) right son=29 (31 obs)
  Primary splits:
      bed1 < 5.5   to the left,  improve=3.237935, (0 missing)
      bcd1 < 5.5   to the left,  improve=3.237935, (0 missing)
      se1  < 383   to the right, improve=1.981407, (0 missing)
      dec2 < 26.5  to the right, improve=1.958122, (0 missing)
      ae1  < 345   to the left,  improve=1.548805, (0 missing)
  Surrogate splits:
      bcd1 < 5.5   to the left,  agree=1.000, adj=1.000, (0 split)
      se1  < 448.5 to the right, agree=0.825, adj=0.645, (0 split)
      ae1  < 345   to the right, agree=0.714, adj=0.419, (0 split)
      bec1 < 5.5   to the left,  agree=0.683, adj=0.355, (0 split)
      ae2  < 346.5 to the left,  agree=0.651, adj=0.290, (0 split)

Node number 15: 60 observations,    complexity param=0.025
  predicted class=3  expected loss=0.4666667  P(node) =0.25
    class counts:    16    12    32
   probabilities: 0.267 0.200 0.533
  left son=30 (30 obs) right son=31 (30 obs)
```

```
  Primary splits:
      ae1  < 335   to the left,  improve=3.733333, (0 missing)
      dec1 < 529.5 to the right, improve=2.716667, (0 missing)
      bed2 < 7.5   to the left,  improve=2.606289, (0 missing)
      bcd2 < 7.5   to the left,  improve=2.018301, (0 missing)
      dcd1 < 583   to the left,  improve=2.002516, (0 missing)
  Surrogate splits:
      pe1  < 1.5   to the left,  agree=0.850, adj=0.700, (0 split)
      ps1  < 0.5   to the right, agree=0.850, adj=0.700, (0 split)
      se1  < 429.5 to the left,  agree=0.683, adj=0.367, (0 split)
      bec2 < 6.5   to the left,  agree=0.650, adj=0.300, (0 split)
      bed2 < 6.5   to the left,  agree=0.617, adj=0.233, (0 split)

Node number 24: 12 observations
  predicted class=1  expected loss=0.08333333  P(node) =0.05
    class counts:    11     0     1
   probabilities: 0.917 0.000 0.083

Node number 25: 27 observations,    complexity param=0.015625
  predicted class=1  expected loss=0.5185185  P(node) =0.1125
    class counts:    13     3    11
   probabilities: 0.481 0.111 0.407
  left son=50 (20 obs) right son=51 (7 obs)
  Primary splits:
      ae2  < 17.5  to the left,  improve=3.368783, (0 missing)
      se2  < 161.5 to the left,  improve=2.370370, (0 missing)
      ae1  < 365.5 to the right, improve=2.111640, (0 missing)
      se1  < 401.5 to the right, improve=1.983069, (0 missing)
      ded2 < 1705  to the left,  improve=1.482744, (0 missing)
```

```
  Surrogate splits:
      se2  < 188   to the left,  agree=0.889, adj=0.571, (0 split)
      dcd1 < 2316  to the left,  agree=0.852, adj=0.429, (0 split)
      bec1 < 6.5   to the left,  agree=0.815, adj=0.286, (0 split)
      bed1 < 6.5   to the left,  agree=0.815, adj=0.286, (0 split)
      se1  < 387   to the right, agree=0.815, adj=0.286, (0 split)

Node number 28: 32 observations
  predicted class=2  expected loss=0.34375  P(node) =0.1333333
    class counts:     5    21     6
   probabilities: 0.156 0.656 0.188

Node number 29: 31 observations,    complexity param=0.028125
  predicted class=3  expected loss=0.5806452  P(node) =0.1291667
    class counts:     9     9    13
   probabilities: 0.290 0.290 0.419
  left son=58 (16 obs) right son=59 (15 obs)
  Primary splits:
      dec2 < 52.5  to the right, improve=3.247581, (0 missing)
      dec1 < 62    to the right, improve=2.246390, (0 missing)
      spc  < 1.5   to the right, improve=2.074717, (0 missing)
      bec1 < 5.5   to the right, improve=1.677126, (0 missing)
      bed1 < 6.5   to the right, improve=1.459333, (0 missing)
  Surrogate splits:
      dec1 < 62    to the right, agree=0.806, adj=0.600, (0 split)
      bec1 < 5.5   to the right, agree=0.774, adj=0.533, (0 split)
      bec2 < 2.5   to the left,  agree=0.677, adj=0.333, (0 split)
      ded2 < 1666  to the right, agree=0.677, adj=0.333, (0 split)
      dcd2 < 2026  to the right, agree=0.677, adj=0.333, (0 split)
```

```
Node number 30: 30 observations,    complexity param=0.025
  predicted class=1  expected loss=0.6  P(node) =0.125
    class counts:    12     8    10
   probabilities: 0.400 0.267 0.333
  left son=60 (17 obs) right son=61 (13 obs)
  Primary splits:
      dec2 < 388.5 to the right, improve=3.679035, (0 missing)
      bec1 < 6.5   to the right, improve=2.907937, (0 missing)
      dec1 < 618.5 to the right, improve=2.780952, (0 missing)
      se2  < 422   to the right, improve=2.604147, (0 missing)
      bed2 < 5.5   to the left,  improve=2.217805, (0 missing)
  Surrogate splits:
      dec1 < 340.5 to the right, agree=0.933, adj=0.846, (0 split)
      bed1 < 4.5   to the right, agree=0.833, adj=0.615, (0 split)
      bcd1 < 4.5   to the right, agree=0.833, adj=0.615, (0 split)
      bec1 < 5.5   to the right, agree=0.800, adj=0.538, (0 split)
      ae1  < 180   to the right, agree=0.800, adj=0.538, (0 split)

Node number 31: 30 observations
  predicted class=3  expected loss=0.2666667  P(node) =0.125
    class counts:     4     4    22
   probabilities: 0.133 0.133 0.733

Node number 50: 20 observations
  predicted class=1  expected loss=0.35  P(node) =0.08333333
    class counts:    13     1     6
   probabilities: 0.650 0.050 0.300
```

```
Node number 51: 7 observations
  predicted class=3  expected loss=0.2857143  P(node) =0.02916667
    class counts:     0     2     5
   probabilities: 0.000 0.286 0.714

Node number 58: 16 observations
  predicted class=2  expected loss=0.5  P(node) =0.06666667
    class counts:     5     8     3
   probabilities: 0.312 0.500 0.188

Node number 59: 15 observations
  predicted class=3  expected loss=0.3333333  P(node) =0.0625
    class counts:     4     1    10
   probabilities: 0.267 0.067 0.667

Node number 60: 17 observations
  predicted class=1  expected loss=0.3529412  P(node) =0.07083333
    class counts:    11     3     3
   probabilities: 0.647 0.176 0.176

Node number 61: 13 observations
  predicted class=3  expected loss=0.4615385  P(node) =0.05416667
    class counts:     1     5     7
   probabilities: 0.077 0.385 0.538
```

C.4.3 Summary of Type Prediction Model with Subset

```
rpart(formula = opt ~ bec1 + bed1 + bcd1 + bec2 + bed2 + bcd2 +
    pe1 + pc1 + pe2 + pc2 + ps1 + ps2 + trf + ae1 + ae2 + se1 +
```

```
    se2 + dec1 + ded1 + dcd1 + dec2 + ded2 + dcd2, data = trainingData,
    method = "class")
  n= 224

          CP nsplit rel error    xerror       xstd
1 0.53571429      0 1.0000000 1.2142857 0.06526326
2 0.04910714      1 0.4642857 0.4821429 0.05715830
3 0.03125000      4 0.3035714 0.5089286 0.05820411
4 0.01000000      6 0.2410714 0.4821429 0.05715830

Variable importance
 ae1  pe1  ps1 dec2 dec1  se1 ded1 ded2  ae2 dcd1 bec1  pe2  se2  pc1  ps2
  20   19   16   11   10   10    3    2    2    2    2    1    1    1    1

Node number 1: 224 observations,    complexity param=0.5357143
  predicted class=0  expected loss=0.5  P(node) =1
    class counts:   112   112
   probabilities: 0.500 0.500
  left son=2 (154 obs) right son=3 (70 obs)
  Primary splits:
      pe1  < 1.5    to the right, improve=37.40260, (0 missing)
      ae1  < 254.5  to the right, improve=37.40260, (0 missing)
      ps1  < 0.5    to the left,  improve=34.03509, (0 missing)
      dec1 < 13     to the left,  improve=31.45492, (0 missing)
      dec2 < 71.5   to the left,  improve=19.77855, (0 missing)
  Surrogate splits:
      ae1  < 254.5  to the right, agree=1.000, adj=1.000, (0 split)
      ps1  < 0.5    to the left,  agree=0.951, adj=0.843, (0 split)
      se1  < 358.5  to the right, agree=0.839, adj=0.486, (0 split)
```

```
      pc1  < 2.5    to the right, agree=0.701, adj=0.043, (0 split)
      dcd1 < 3503.5 to the left,  agree=0.701, adj=0.043, (0 split)

Node number 2: 154 observations,    complexity param=0.04910714
  predicted class=0  expected loss=0.3051948  P(node) =0.6875
    class counts:   107    47
   probabilities: 0.695 0.305
  left son=4 (58 obs) right son=5 (96 obs)
  Primary splits:
      dec1 < 33.5   to the left,  improve=11.955370, (0 missing)
      dec2 < 78.5   to the left,  improve= 7.573901, (0 missing)
      ae2  < 111.5  to the right, improve= 6.476204, (0 missing)
      se2  < 334    to the right, improve= 5.613649, (0 missing)
      bec1 < 4.5    to the right, improve= 5.221337, (0 missing)
  Surrogate splits:
      dec2 < 78.5   to the left,  agree=0.948, adj=0.862, (0 split)
      ded1 < 783    to the left,  agree=0.773, adj=0.397, (0 split)
      ded2 < 333    to the left,  agree=0.714, adj=0.241, (0 split)
      pe2  < 3.5    to the right, agree=0.701, adj=0.207, (0 split)
      bec1 < 5.5    to the left,  agree=0.682, adj=0.155, (0 split)

Node number 3: 70 observations
  predicted class=1  expected loss=0.07142857  P(node) =0.3125
    class counts:     5    65
   probabilities: 0.071 0.929

Node number 4: 58 observations
  predicted class=0  expected loss=0.05172414  P(node) =0.2589286
    class counts:    55     3
```

```
   probabilities: 0.948 0.052

Node number 5: 96 observations,    complexity param=0.04910714
  predicted class=0  expected loss=0.4583333  P(node) =0.4285714
    class counts:    52    44
   probabilities: 0.542 0.458
  left son=10 (79 obs) right son=11 (17 obs)
  Primary splits:
      dec2 < 114    to the right, improve=5.510300, (0 missing)
      dec1 < 314.5  to the left,  improve=2.715668, (0 missing)
      ae2  < 311.5  to the right, improve=2.083333, (0 missing)
      se1  < 432.5  to the left,  improve=2.083333, (0 missing)
      se2  < 410.5  to the right, improve=2.083333, (0 missing)
  Surrogate splits:
      pc2  < 2.5    to the right, agree=0.854, adj=0.176, (0 split)
      dec1 < 111.5  to the right, agree=0.854, adj=0.176, (0 split)
      se2  < 153.5  to the right, agree=0.844, adj=0.118, (0 split)
      ded1 < 373.5  to the right, agree=0.844, adj=0.118, (0 split)

Node number 10: 79 observations,    complexity param=0.04910714
  predicted class=0  expected loss=0.3797468  P(node) =0.3526786
    class counts:    49    30
   probabilities: 0.620 0.380
  left son=20 (44 obs) right son=21 (35 obs)
  Primary splits:
      dec1 < 314.5  to the left,  improve=6.097008, (0 missing)
      dec2 < 238.5  to the left,  improve=4.440486, (0 missing)
      ae1  < 330.5  to the right, improve=2.857614, (0 missing)
      se1  < 518.5  to the right, improve=2.215190, (0 missing)
```

```
    trf  < 1.5    to the right, improve=1.778010, (0 missing)
  Surrogate splits:
    dec2 < 352    to the left,  agree=0.886, adj=0.743, (0 split)
    se1  < 432.5  to the left,  agree=0.671, adj=0.257, (0 split)
    dcd1 < 881    to the right, agree=0.658, adj=0.229, (0 split)
    bec1 < 2.5    to the right, agree=0.646, adj=0.200, (0 split)
    ded1 < 1524.5 to the left,  agree=0.646, adj=0.200, (0 split)

Node number 11: 17 observations
  predicted class=1  expected loss=0.1764706  P(node) =0.07589286
    class counts:     3    14
   probabilities: 0.176 0.824

Node number 20: 44 observations
  predicted class=0  expected loss=0.2045455  P(node) =0.1964286
    class counts:    35     9
   probabilities: 0.795 0.205

Node number 21: 35 observations,    complexity param=0.03125
  predicted class=1  expected loss=0.4  P(node) =0.15625
    class counts:    14    21
   probabilities: 0.400 0.600
  left son=42 (24 obs) right son=43 (11 obs)
  Primary splits:
    ae1  < 335    to the right, improve=3.065152, (0 missing)
    bed1 < 6.5    to the right, improve=1.728571, (0 missing)
    se1  < 502    to the right, improve=1.728571, (0 missing)
    dcd2 < 1614   to the left,  improve=1.568519, (0 missing)
    ae2  < 311.5  to the right, improve=1.556579, (0 missing)
```

```
  Surrogate splits:
      pe1  < 2.5    to the right, agree=0.743, adj=0.182, (0 split)
      ps1  < 0.5    to the left,  agree=0.743, adj=0.182, (0 split)
      ae2  < 365    to the left,  agree=0.743, adj=0.182, (0 split)
      dec1 < 338    to the right, agree=0.743, adj=0.182, (0 split)
      dcd1 < 1379.5 to the left,  agree=0.743, adj=0.182, (0 split)

Node number 42: 24 observations,    complexity param=0.03125
  predicted class=0  expected loss=0.4583333  P(node) =0.1071429
    class counts:    13    11
   probabilities: 0.542 0.458
  left son=84 (9 obs) right son=85 (15 obs)
  Primary splits:
      ae2  < 311.5  to the right, improve=3.472222, (0 missing)
      dcd2 < 1400.5 to the left,  improve=2.002381, (0 missing)
      dcd1 < 551.5  to the right, improve=1.294818, (0 missing)
      bcd1 < 2.5    to the left,  improve=1.041667, (0 missing)
      se1  < 490    to the right, improve=1.041667, (0 missing)
  Surrogate splits:
      se2  < 454    to the right, agree=0.792, adj=0.444, (0 split)
      dec2 < 1363   to the right, agree=0.792, adj=0.444, (0 split)
      ps2  < 0.5    to the left,  agree=0.750, adj=0.333, (0 split)
      dec1 < 435.5  to the left,  agree=0.750, adj=0.333, (0 split)
      ded2 < 2566.5 to the right, agree=0.750, adj=0.333, (0 split)

Node number 43: 11 observations
  predicted class=1  expected loss=0.09090909  P(node) =0.04910714
    class counts:     1    10
   probabilities: 0.091 0.909
```

```
Node number 84: 9 observations
  predicted class=0  expected loss=0.1111111  P(node) =0.04017857
    class counts:     8     1
   probabilities: 0.889 0.111

Node number 85: 15 observations
  predicted class=1  expected loss=0.3333333  P(node) =0.06696429
    class counts:     5    10
   probabilities: 0.333 0.667
```

C.4.4 Summary of Option Prediction Model without Subset

C.4.5 Summary of Lateral Option Prediction Model

C.4.6 Summary of Vertical Option Prediction Model

C.4.7 Summary of Speed Option Prediction Model

APPENDIX D
LITERATURE REVIEW

D.1 Air Traffic Control Systems and Controllers

It is essential to understand the history of air traffic control to understand how the CD&R evolved. Since pilots could avoid other aircraft easily during the operations, focuses on air traffic control in the early days were on managing landings and take-offs from runways. Earlier runways had a different shape and usages, because the aircraft did not need a long runway to take-off and land, and they could land and take-off from any direction. If there were multiple aircraft trying to land or depart from an airport, pilots had to continuously monitor both runways and air to figure out when and how to take the actions. This process became more complicated by severe weather that limited the landing and take-off directions. Thus, it was clear that they need some safety system to manage the traffic to avoid an accident.

ATCos manually operated the first form of air traffic control. They had two different flags at the runways and used the flags to signal different information to the aircraft. Maneuvering advice was simple; they guided approaching or taking-off aircraft to either proceed or hold until the next signal. This system helped to improve the air traffic at that time but had a critical drawback. It was inefficient because a person had to stand on the runway. The person could be hard to be noticed and might have difficulties giving instructions to specific aircraft when there are multiple of them. Moreover, this system was almost impossible to use during the harsh weather conditions and night time.

The traffic management system needed a more reliable method. Instead of mono-toned and single-colored flags, controllers utilized colored ones but could not solve all issues. Before the end of the 1930s, they implemented a new method; light gun signals. With distinct colors and signals, controllers aim specific aircraft with the device and instruct them. To utilize this device more efficiently, they installed the devices on high grounds that function as current control towers. Current air traffic control system still operates the light signals and have not changed significantly.

As the control towers became a standard, Cleveland Airport started a milestone of current air traffic control system. They constructed a tower equipped with devices that transmit and receive radio signals. It allowed them to use voice communication with aircraft equipped with the same type of devices. Thus, controllers could directly communicate with properly equipped aircraft and provide detailed instructions. In a brief time of period, the air traffic control system was dramatically improved. However, the conflict detection and resolution were still unreliable due to lack of technologies and regulations. Radio devices were high-end, bulky, and expensive technologies. The system stabilized as aircraft designers produce better planes.

Airline companies established the first form of the modern air traffic control system, airway traffic control units (ATCUs) because the government was not able to prepare the system in time [1]. Employees from airlines were dispatched to the units, and with mutual agreements among them, the units took responsibilities on separating aircraft within assigned regions. Due to lack of technologies, communication between a unit and the pilot was not reliable. Thus, they had to take a different approach. First, the units collected flight plans of the day from each airline dispatchers. They put the information all together and determined time and directions for the take-offs. Also, if they detect possible conflict during en-routing, they advised those aircraft to take dedicated maneuvers to avoid an accident. Additionally, aircraft equipped with radio devices were asked to update their position to increase an accuracy of the traffic control.

Later, this conflict detection and resolution method were standardized to a paper strip method that operated by federal air traffic controllers [2]. This method uses paper strips (or shrimp boat) that indicates aircraft and position it on a board with other strips to represent their progress. They updated information every 10 minutes by either position reports from pilots or predictions. Due to gaps between the information updates and uncertainties on their locations, ATCos had to separate each aircraft by 10 minutes to each other, which assigned about 50 to 100 miles between aircraft. At the same time, concepts of active and passive control were unintentionally exercised by the controllers. In the severe weather conditions, ATCos expected that pilots could not identify each other on their sights. So ATCos should provide detailed instructions to avoid the mid-air collisions.

The World War II and events after the war dramatically affected the air transportation system. Not only the technical improvements (specifically radar and radio technologies), its demand was skyrocketed as civilians consider air transportation as a reliable and efficient method. The conventional air traffic control system hit its capacity, and they had to modify the system [54]. As a result, in 1948, the government reported a need for not only a safer traffic control system, but also with better traffic flow. To meet the requirements, researchers adopted radio and radar technologies to establish a radar-based surveillance system that became the foundation of the modern aircraft tracking system. From the 1960s, aircraft designers introduced jet aircraft, and they started to replace old models. This new type of aircraft changed the paradigm of not only air traffic control but also the whole air transportation system. Airports and runways must be modified to meet the requirements to take-off and land the jets. Due to exceedingly increased airspeed, ATCos were not able to follow them manually anymore. Thus, they needed an automated system to handle the traffic. As a response to the changes, President Kennedy ordered FAA to modernize the air traffic control system known as Project Bacon [55]. Studies from this project standardized and modernized the conventional system with new radar and automated data processing systems.

Since then ATCos operate semi-automated traffic control system to detect conflicts and provided resolutions manually. Since the beginning of the air traffic control system, this function is still left to be manually operated by ATCos. However, an event in 1981 triggered a high demand for automated conflict detection and resolution; PATCO Strike [56]. The airline industry in the U.S. was deregulated from 1978. As an immediate effect, the number of aircraft increased, which increased the workload of ATCos. Since the 1960s their workload became an issue, and they had a high tension with the government due to it. As a result, they formed a union the Professional Air Traffic Controllers Organization (PATCO). Laboring conditions of ATCos became worse as the air transportation expands and the government reduces their budgets. After all, the tension between them caused the illegal strike in 1981 resulting most of the ATCos to lose their jobs. Eventually, this action increased their workload even more due to the reduced number of the controllers and people realized they would need a system to reduce the workload of ATCos.

Since the foundation of air transportation system, each subsystem including ground facilities, aircraft, equipment, and people took more sophisticated technologies, tasks, and forms and integrated together to establish National Airspace System (NAS). Communication, navigation, and surveillance (CNS) equipment not only allowed the sophisticated form of the current systems but also bond them together. Especially, radar and radio communication equipment take the most critical role in this link.

According to the Air Traffic Control Handbook by FAA, we can categorize the operation of aircraft into four phases; taxiing, taking-off, en-routing, and landing [57]. There are different control systems for each phase, and their equipment is mostly ground-based ones except for the ones in aircraft. Also, NAS operates different types of radars for each phase due to a trade-off between range and accuracy of scanning function. Radars with more extended scanning range have relatively less accuracy compare to the short-range ones. Generally, long-range radars take more than 10 seconds to refresh the information while the shorter ones take less than 5 seconds. As space is more congested, ATCos utilize shorter and more accurate radar systems to manage the traffic.

Taxiing, taking-off and landing phases belong to an airport control system [58]. This system has two primary operations for each phase operated by airport control towers; ground and local controls. Control towers manage their airports and 5 to 10 nautical miles of local airspace. Due to airspace classifications, aircraft having business with an airport will only enter its local airspace. Thus, an airport control tower should manage traffic near it. The only difference with earlier years is that the responsible airspace became broader and varied by the airport. We consider taking-off and landing as the most critical phase of the aircraft operation. One of the reason is the congestion at the airports' airspaces. Thus, precise monitoring of all aircraft activity near the airport is the essential function. Generally, the towers control movements of aircraft by very or ultra-high frequency radio communication. A busy airport like JFK utilizes surface movement radars such as Airport Surface Detection Equipment (ASDE-X) that visualize all aircraft movements on the ground [59]. It collects information from the radar on the towers and the sensors around the airports. According to FAA, 35 US airports equipped the device. For the take-offs and landings, airports operate terminal radar approach control (TRACON). The radar monitors about up to 50 nautical miles from the airport. If multiple airports are located closely together, an integrated facility provides services to them. For the en-routing, ATCo monitors aircraft with long-range radars that are capable of seeing longer than 100 nautical miles. The radars are located at facilities called air route traffic control centers (ARTCC) where ATCos also manage the en-routing traffic.

Even an airport is equipped with ASDE-X, the tower controllers perform most of their airport traffic duties through verbal radio communication. In general aviation, aircraft must receive a clearance, approving its flight plan, from an ATCo as a first step. To leave an airport, the tower controller gives a departure instruction. This instruction includes designated runway and heading including specific instruction on how to enter its planned route. Smaller airports without radars solely depend on visual and verbal communication to perform this procedure. Both pilots and ATCo must visually check whether the heading airspace is cleared to depart. The tower controller must visually confirm that an aircraft can enter a designated runway and clear to take-off. If pilots need to perform a different approach to enter its planned route, they must notify the towers. Busier airport utilizes ASDE-X to digest a substantial number of aircraft in brief time. This system not only tracks aircraft on the ground, but it also predicts possible conflicts. Even if there is a traffic control supporting tool, the tower controllers must check the ground visually. Landing procedure is reversing the departing one with one additional procedure. If there is no cleared runway, ATCo asks an aircraft to hold. If there are multiple aircraft on hold, ATCo put following orders to aircraft considering several priority aspects including fuel, flight hours, and emergency situations in the aircraft.

The first procedure after taking off from an airport and about to leave its airspace boundary is the transfer of control. The tower controller (transferring controller) passes, handoff, its duty on the aircraft to the receiving controller at an ARTCC. Two controllers must communicate with an aircraft pass the border to ensure that the receiving controller to be aware of oncoming traffic. Right after the communication, the transferring controller instructs the aircraft to communicate with the receiving controller and terminates the communication with the aircraft. However, the aircraft is still under control of the controller until it physically leaves the airspace. Unlike the tower controllers, ATCos at ARTCC do not perform visual monitoring. Their traffic controls solely rely on weather and flight data on their display and information received from pilots. If ATCo must alter a route for any reason including aircraft separation, ATCo provides a maneuvering instruction to an aircraft. To assure its process, ATCo may ask the pilot to report the progress. This procedure continues until the handoff. If their radar system malfunctions, they switch the method to the old shrimp boat one.

D.2 Flight Tracking Data

Modern aircraft have various sensors that collect information representing the status of aircraft such as airspeed. This information is commonly called as avionic data. Along with the avionic data, there is other information such as the flight plan that initially generated from ground stations and carried by the corresponding aircraft. Flight plan can be accessed independently, but other avionic information only can be accessed through communicating with aircraft both manually and automatically. FlightAware is an online flight data provider that collects various flight information from air traffic control systems in various companies and other resources including their own facilities. One of its services is providing locational information about en-routing aircraft with their flight plan in real time. The flight plan, open-loop data, is represented as a set of coded locations called waypoints. According to the plan, aircraft should pass these points while heading to their destinations. However, actual flight trajectories are not usually identical to connecting the waypoints. The actual trajectories are called as the closed-loop data. It is collected in an approximately 30-second interval and contains physical status information such as coordination, heading and pitching, and speed. Due to errors in recordings by the sensors and/or the communication, collected data from the provider can be may be incorrect or missed.

D.3 Empirical Studies of ATCo

D.3.1 Task Analysis

The first step of studying a human operator in a system is understanding the job. It requires methods to collect, classify, and interpret data on human performance in work situations and a collection of these methods is task analysis [60]. It has many methods to describe a work regarding behavioral and mental tasks. For example, hierarchical task analysis developed by Annett et al., 1971 models a task with its sub-tasks in hierarchical and sequential order to achieve the goal [61]. This section briefly discusses behavioral and workload analysis and focuses on the analysis of the mental side.

Air Traffic Control Handbook states rules and tasks that ATCos must follow. However, it only provides a minimum amount of information about their tasks such as what is the clearance and its procedures. ATCos perform their tasks using various equipment, and their tasks are slightly different depends on their positions. For example, tower controllers' tasks are about guiding aircraft to take-off and land, while en-route ATCos separate aircraft. Thus, there are studies focused on understanding ATCo operations in detail by general task analysis [62–66]. However, traditional analysis on their task has an explicit limitation in understanding how they perform the tasks [67]. Also, there are researchers on mental aspects of the tasks; Wickens applied psychologies to engineering field to understand how human operators perform tasks cognitively [68]. These researchers adapted cognitive task analysis on ATCos to model their mental processes of aircraft conflict prediction, detection, and resolution. Cognitive task analysis is the extension of traditional task analysis methods such as the hierarchical task analysis to conduct information about the knowledge, thought processes, and goal structures from the target task [69].

Information from separating and focusing on the mental side of the task itself does not have industrial value to understand, modify, or enhance the task performance. Its primary purpose is on application to develop a performance enhancement method. For example, Starter and Woods, 1995 conducted the study to identify mode errors and Wise, 2012 did for the system issues. Another application is measuring their workload. The workload of ATCos is an important research topic for a long time since 1978. Their task became more intense as the number of aircraft increase. As stated previously, safety is the essential factor of the air traffic control system, which is dependent on ATCo performance. A human can occur when we are in abnormal conditions. It is a well-known fact that ATCos have high workload and stress due to their responsibilities and a significant amount of air traffic [70]. As an extension to studying ATCos tasks, researchers attempt to measure their workload to evaluate their tasks, which can provide necessities of automation to support their tasks and reduce the workload. At this point, we only know ATCos have a high workload, but we still do not have a method with zero defects.

Lack of understanding on ATCos is one of the reasons for the slow progress. Following sections summarizes current progress on the understanding ATCos. Sections discuss findings from studies regarding generally accepted, debatable, and inconclusive ones.

Cognitive task analysis is based on theories of psychology regarding how brain perceive, process information to make decisions and take actions. Thus, cognitive analysis of air traffic controllers is also adapting conventional physiological explanations of brain functions, and researchers generally agree on them. Figure D.1. Illustrate a generic cognitive task model of air traffic controllers in global level regardless of their positions and following paragraphs explain the model in detail [29].

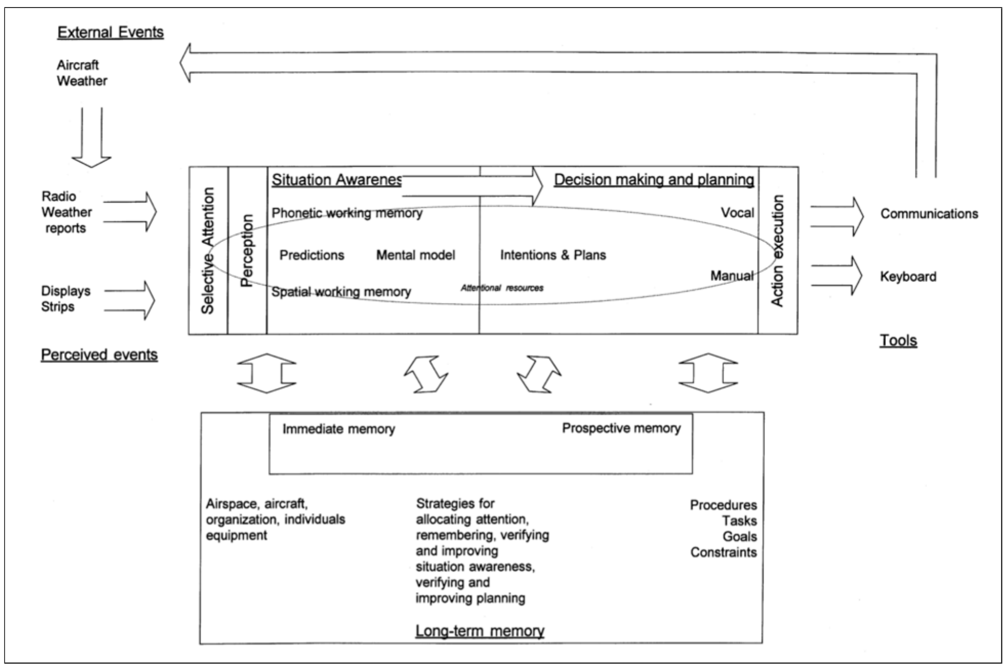


Figure D.1.: Genetic Cognitive Model of Air Traffic Controller Task [ref]

At the very top level, the model shows their mental process is triggered by events such as movements of aircraft, incoming radio communications, and weather changes. ATCos take the events as information and perform five cognitive stages; selective attention, perception, situation awareness, planning and decision-making, and action execution. As the events trigger the processes, their action is a result of trained air traffic control procedures and practical and spontaneous strategies. Hopkin, 1995, called this mental process as the "picture," which ATCos draw on their mind by perceiving information from equipment such as a radar display, radio device, documents, and telephone with the corresponding airspace and project them to predict the future [71].

The model has process flow direction and iterative. The process flows in one direction and end of one cycle triggers the next cycle. It is related to their duties, changes in the conditions in an airspace, and information update rate through their equipment. If there is an aircraft in an assigned airspace, they have to monitor the aircraft until it leaves. Even though the process is sequential and repetitive, ATCos may skip a stage if it is unnecessary. For example, if there is no aircraft to monitor, ATCo does not need to draw the picture or predict the future at the moment. Also, they make decisions based on the experience. In this case process of decision-making and planning becomes simpler.

General agreements on how ATCos acquire information from the external events related to the types of information they perceived and what it can trigger from skilled operators. All ATCo involved activities like aircraft clearance occur at the outside of the working environment whether ATCos work at airport control towers or air traffic control centers. ATCos gather information to perform most of the activities through their equipment which requires visual and auditory senses. Radar displays show changes of aircraft status and movements and other information comes from pilots and other agents through their voices. It is considered as capturing visual and auditory changes because they can acknowledge the current situation only two types of sources. However, they do not take the information as it is. Moray, 1986 stated that operators select information that they need so that they do not have to spend a time to take all information available at that time, which is called selective attention [72]. With selective attention, operators know where to find information efficiently. Also, researchers observed selective attention from the experts more frequently than novices. It implies accumulated experience help distinguishing critical information from others. At the same time, it is possible that the selected information is not available to the operator due to malfunctioning of equipment, etc. Apart from selecting information, some types of information itself generate another information. Monan, 1988 found that ATCos expect a continuation of the current aircraft movement when they perceive the information [73]. So ATCos expect aircraft to keep their current airspeed, heading, and altitude. Also, Schank and Abelson, 1977 stated that specific information expects them to predict next incoming information [74]. For example, if an aircraft shows up at one's airspace, corresponding ATCo expect radio communication from the pilot.

As shown in Figure D.1, stages for processing the perceived information have subelements. This section discusses all elements except for the mental model, which is reviewed in the following section. Researchers generally agree that perceived information goes to working memory. According to its definition from Miyake and Shah, 1999, working memory is the part of short-term memory that is a cognitive system with limited capacity in holding information to process [75]. Also, Baddeley, 1986 stated that it is the "workbench" in the human brain [76]. Information in the working memory is either verbal and spatial. For air traffic controller task, information received from communications with pilots correspond to the verbal memory that ATCos can speak [77]. Logie, 2014 state spatial working memory of ATCoS is representations of their airspace in their minds [78]. Researchers believe that the spatial memory once must be transformed from the verbal one because ATCos should read the radar displays in two-dimensional space and project it to three-dimensions with digitally presented altitude related factors.

Researchers agree on processing working memory occurs at situation awareness of ATCos. Endesely, 1996 defined situation awareness as a level of understanding status of a situation, but also eligibility to project it to its future status [63]. After working memory receives the information, the memory interprets it based on the knowledge stored in long-term memory. Memory checks whether the information matches or related with the stored memory and retrieves associated responses. For example, if ATCo faced similar weather condition before, he/she will execute similar maneuvers to aircraft. Seamster et al., 1993 stated ATCos utilize working memory to comprehend the perceived information and make predictions based on it and these activities are to understand the current situation which is considered as situation awareness [79]. Thus, situation awareness of ATCos includes not only understanding the trajectories of aircraft and related traffic in assigned airspace sectors with expected future trajectories including possible changes due to external factors like weather. Also, understanding on circumstances of ATCos themselves and their goals of the traffic control tasks become parts of the situation awareness.

Researchers generally agree that knowledge stored in the long-term memory plays an important role in processing perceived information in the working memory. According to Redding et al., 1992, knowledge stored in the long-term memory is about the assigned airspace, equipment, rules, procedures, weather, and specifics of various aircraft [80]. For example, ATCo knows geological characteristics of the assigned airspace sector, air routes, and its boundaries. Also, they know how to operate the equipment such as radar displays and radio communication device. Since they know specifics and dynamics of various aircraft, they can instruct specified maneuvers that an aircraft can execute.

Another characteristic of the long-term memory that researchers agree is an impact of domain experience to the memory. From the psychological perspectives on the memory of experts, Chi et al., 1981 stated that experience helps long-term memory to form more efficient memory structures for multiple events [81]. If an ATCo identified a potential aircraft conflict pair, he/she must make decisions and instruct maneuvers to the pilots. Before this step, ATCo needs to choose a solution from candidates, which are results of processing working and long-term memory under situation awareness. Details of a conflict resolution maneuver refer from their experience including trained procedures from their long-term memory. Novices tend to resolve a case one by one, while experts can perform multiple ones at once [79]. If an encountered case is novel and cannot retrieve related knowledge from the long-term memory, ATCos simulate the situation in their working-memory and frequency of this case decrease, or it can be shortened as they become more experts.

Not only to generate the candidates but also the decision-making and planning stage is dependent on the long-term memory. Figure D.1. Show that after the stage of situation awareness where ATCos formulate decision candidates, the cognitive process moves to the decision-making stage. As previously stated, the long-term memory of ATCos include procedures established by training and experience. Hopkin, 1988 and Vidulich et al., 2010 stated traffic control procedures, rules, and risks in the long-term memory of ATCos such as minimum separation distance and uncertainties under different conditions become standards of decision-making process [82, 83].

According to Harris and Wilkins, 1982, results of the decision-making process stage have three categories; an immediate, strategic, or series [84]. The strategic decision is planning the future executions and researchers agree that most of the en-route traffic maneuvers are strategic decisions. Strategic requires prospective memory ability from ATCos because they need to remember to execute a specific maneuver at a specific time. Also, researchers believe the prospective memory plays essential rule on monitoring changes of aircraft movement. For example, if an ATCo guides an aircraft to change its attitude to a degree, he/she is very likely to check later when the aircraft is expected to reach that state.

The last characteristic of generally agreed long-term memory is its adaptation and self-evolution. Many phycologists [79, 85, 86]. The long-term memory builds strategies and develops them over time. The researchers stated these strategies improves and customizes themselves to specific purposes resulting in the cognitive stages to become more efficient and they are effective when the volume of work is high. Gopher, 1993 and Stein, 1993 found attention allocation strategies of ATCos on the external events help them to handle a high volume of events [85, 87] and there are strategies to prioritize tasks so that ATCos can handle a large amount of work more effectively [88]. Opposite to customized strategies, there are higher level strategies for handling complex and time-sensitive tasks. This type of strategies allows practitioners to understand and figure out how to manage the situation within given conditions. In the air traffic control, methods to avoid or resolve multiple conflicts correspond to it [89–92]. Lastly, strategies in the long-term memory can affect not only the cognitive processes but also other types of memory. The long-term memory may include strategies to remember information in the prospective memory. These strategies called as memorization method and the card counting one of the important strategies.

The tasks of ATCos, external events, and their cognitive process is meaningless unless they are willing to perform the tasks by utilizing the external events in their cognitive processes. This willingness is attentional resources. Researchers generally agree that their attention to their duties, environments, and external events is another critical input to the air traffic control tasks. Researchers believe attention require cognitive resources and there are four factors of an event that affect consumption of the resources [29]. Higher frequency of event occurrence and its complexity increases the consumption, while higher expectable and common event likely reduces the amount of resource consumption. For example, even though a complicated multi-aircraft conflict occurs, ATCos will not spend their resources much if the event is expected or familiar because the similar event happened before. In another hand, even if an event is not so complicated, it can consume more than a reasonable amount of resources if it is unexpected and novel. As shown in the two examples, these four factors can interact with others in many ways, which concludes that it is difficult to define the high frequency and high complexity is always more burden.

Regarding the characteristics of attentional resource consumption, Ramussen, 1986 and Ramussen et al., 1991 stated ATCos tends to minimize the resource consumption by utilizing rule-based and knowledge-based behaviors on the different types of events [93, 94]. For example, if a familiar type of aircraft conflict is expected with low complexity, ATCos tend to perform rule-based behaviors that do not require much attention. If an unexpected event occurs such because of human errors, ATCos initiate knowledge-based behaviors that attempt to understand the situation with their knowledge by approaching in creative ways. This behavior is to minimize consumption of time and the attentional resources. Thus, novice ATCos are not eligible to handle the unexpected events adequately because they do not have enough amount of knowledge to perform such behaviors. It appears as the rule, and knowledge-based behaviors are multi-tool to minimize the resource consumption, but they do not work in a different environment such as different airspace and sectors because they are case specific [95]. Each sector and airspace have a different environment and equipment. Types of aircraft activities also can be different. Thus, events in an unfamiliar environment and external event will not trigger both behaviors. Moreover, if it triggers rule-based behavior, it may cause decision errors.

So far, researchers found that ATCos perform their task with information from external events and their memory. Also, an event that they must process has distinctive characteristics depends on the four factors. Thus, each process requires a different amount of resource consumption, so the amount of workload is also different. So far, any of artificial intelligence successfully perform those activities, which proves human is the best option for now to handle the air traffic. However, it is well known that human performance is vulnerable and can be inconsistency due to factors. Apart from the model of their air traffic control methods, researchers also agree that elements that form their cognitive model can lead to errors. For example, Moray, 1986 sated visual perception of ATCos may cause bias by looking at information long enough regardless of its importance to the corresponding event [72]. Monan, 1988 found that expectations influence their perceptions by incorrectly perceive information as it is the expected information due to routined cognitive processes [73]. Multiple researchers identified that working memory could be disrupted easily causing the operators to make incorrect “picture” [77, 96–98]. Also, researchers showed concerns regarding verbal communications [98–100].

D.3.2 Mental Model

A mental model is a theoretical structure in the cognitive process of a practitioner that refers to his/her learning and concepts about a task. It is a result of organizing different knowledge over time. Researchers have various opinions on the definition of the mental model. According to Rouse and Morris, 1986, it is a set of mechanisms that humans generate; descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states [101]. Norman, 1986 provided a more descriptive definition that it is human nature and it provides predictive and explanatory power for understanding external objects coupled with prior knowledge and understanding, which guide human behaviors [102].

Figure D.2. shows the basic classification structure of the mental model by Rouse and Morris, 1986 [101]. The study noted that metal model has at least two dimensions: nature of model manipulation and level of behavior discretion. The nature of model manipulation is a degree of consciousness on the existence of a mental model, and the level of behavioral discretion is a degree of freedom to a practitioner on performing a task. With current approaches, it is hard to study mental models corresponding to the upper left corner of the diagram because of high freedom in action and low self-awareness.

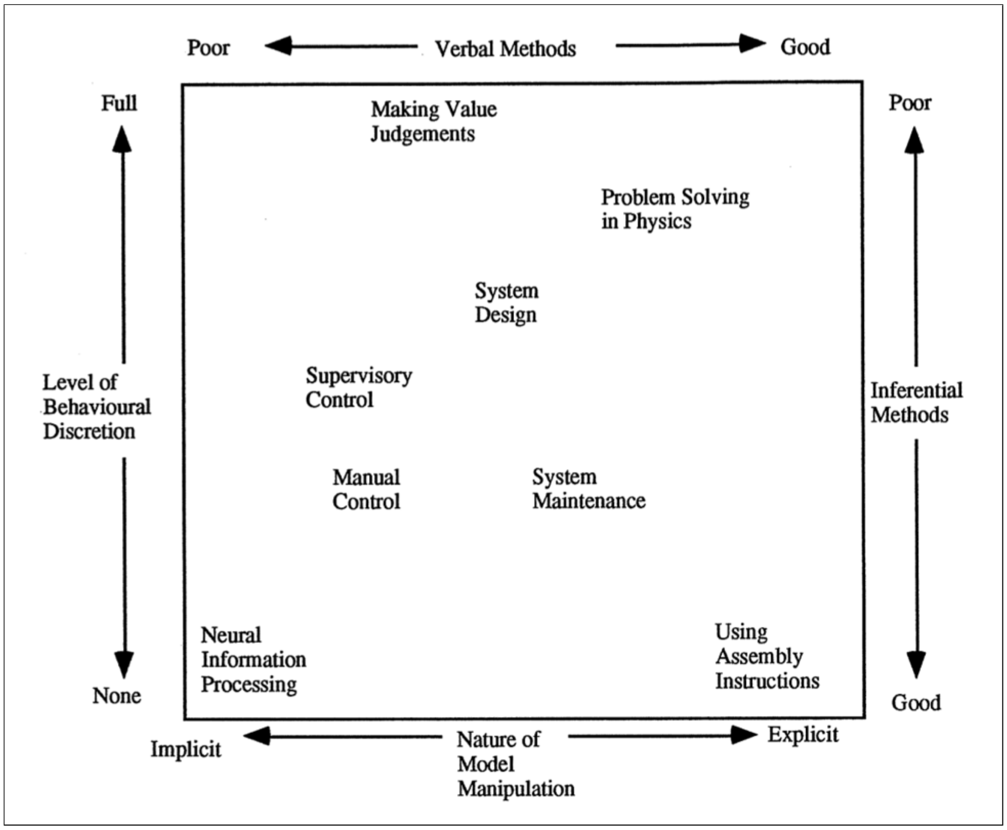


Figure D.2.: Classification of the Mental Model

Besides the classifications, researchers studied other characteristics of the mental model. Rassmussen, 1979 stated mental models have a physical form and function, structure, abstract function, and functional meaning [103]. Also, these characteristics have different levels. Johnson-Laird, 1983 further specified the characteristics; distinguishing mental models with physical and conceptual models [104]. Wilson and Rutherford, 1989 summarized previous studies regarding the characteristics and the noted existence of many mental models for a system having different levels of each characteristic [105].

According to the Rouse and Morris, 1986, there is no clear distinction between situation awareness and mental model [101] and Endsely, 1995 stated that situation awareness is a perception of elements in an environment within a time and space, comprehension of their meaning, and projection of their status in the future [106], which is partially overlapping with definition of the mental model. Wise et al., 2012 specified their relationship; mental model as a basis of situation awareness that takes information from external events through situation awareness and provides internal information back [65].

Researchers applied the concept of the mental model to the air traffic control system in various ways. Vincente, 1988 showed impacts on a user interface of ATCo displays [11]. Concepts of the mental model suggest recalling information experiments on information expected to be in mental models can provide evidence of the mental model existence and other researchers applied the method to identify proof of mental model from ATCos [107–109]. Wise et al., 2012 also suggested that methods to measure characteristics of the model can be applied to evaluate the effectiveness of ATCo equipment and envisioned mental models for the future air traffic control system to be heading toward a higher level of supervisory control [65].

As shown in Figure 1, researchers generally agree the mental model is in the situation awareness stage of the cognitive process. Sarter and Woods, 1991 stated that "mental models could be seen as the basis for adequate situation assessments which, in turn, result in flight-related knowledge that may eventually become part of the pilot's situation awareness. In other words, adequate mental models are one of the prerequisites for achieving situation awareness [11].

Wise et al., 2012 stated that the mental model of ATCo has two different components; domain and device model. The domain model is about airspace, aircraft, and procedures while the device model is understanding of external event information providers such as radar displays. Also, considering characteristics of ATCo tasks, their mental models will correspond to supervisory control and manual control in Figure D.2 because their routine tasks have strong supervisory factors, but occasionally they must give specific instructions to aircraft, which falls into the manual control. Fortunately, conventional experiment methods are eligible to study those types of metal models with some limitations.

The “picture” is a concept that all researchers in this field agree. Whitfield, 1979 interviewed ATCos and concluded that a mental model, the “picture,” exist in their cognitive process and act as a display that its practitioner can freely control to organize perceived information and eventually stimulate task performance [110]. Following studies showed that skilled operators have a clearer “picture,” which is discussed in the later part of this subsection. Even though there was a significant finding, studies in early years were limited. Whitfield, 1979 and Whitfield and Jackson, 1982 only able to interview ATCos [110, 111]. These studies found that at least possesses three different types of information (a static model of the air traffic route structures, separation guidelines, and procedures) and three-dimensional (longitude, latitude, and altitude) representation on the assigned airspace. They suggested that they could identify more aspects of the mental model with other methods and the results may affect enhancing the controllers” working environment. With such limitations in the early stage of research, researchers generally agree that the mental model has various types of information that requires different types of memory to store.

After identification of the picture, Norman first introduced a conceptual mental model of ATCos [112]. However, the model only described radar display related aspects and Niessen et al., 1998 adapted the concept and applied a complete form of the model as shown in Figure D.3 [14]. The researchers named it Modell der Fluglotsenleistungen (MoF1), and researchers continued the mental model study based on this one [113–115].

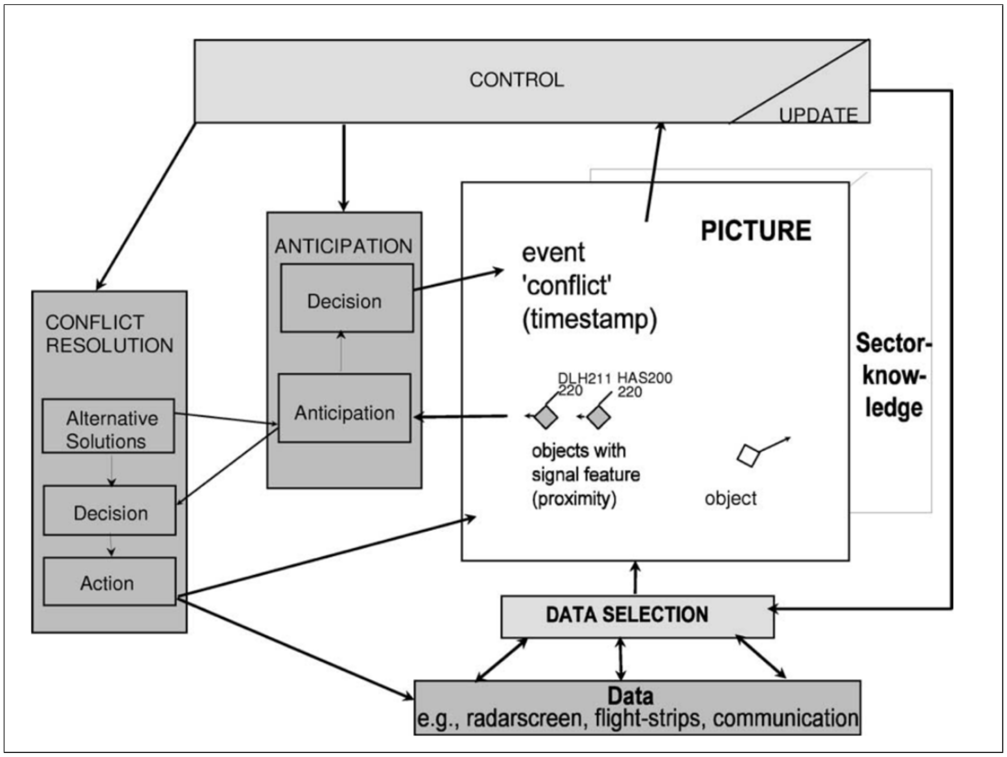


Figure D.3.: Modell der Fluglotsenleistungen (MoF1)

The picture has objects that are representations of aircraft in the assigned airspace. Environments of the picture depend on five different modules: data selection, anticipation, conflict resolution, update, and control. These modules have unique functions and different procedure sequences for three information processing cycles: monitoring, anticipation, conflict resolution cycles.

The monitoring cycle is a procedure to update information in the picture by scanning the external events. The cycle starts with the data selection. The process selects data from perceived information considering required information to the picture then update the information of the picture. Gradually, the picture keep builds up. This procedure is based on the concept of perceiving information from external events to understand the current situation from Endsley, 1996 [63].

Anticipation cycle uses this updated information regarding the aircraft in the picture to predict the future. The cycle compares aircraft in the picture and predict their future state and make a decision whether there will be a conflict or not. This process further explained in four steps sequentially. First, the operator compares pair or more of aircraft at once to see if they are on the same or crossing path. If they do, then the operator checks their altitudes. Second, the operator continues to evaluate the aircraft by predicting their future state to check whether the loss of separation will occur. Third, the operator evaluates the accuracy of the result from the previous step. Last, the operator assesses available time to make a resolution plan and execute it.

Conflict resolution cycle develops a resolution maneuver for the predicted event from the previous cycle, which occurs in the control module. It starts with listing all predicted conflicts in order from the most urgent to the least. Then it generates a novel solution or refers to the previous events. With the candidate solutions, the operator simulates the changes in the future from the picture. The purpose of the simulation is not only to check whether the solution is viable but also whether it will cause another conflict. After the simulation, the operator decides a solution and execute it.

There are researches on characteristics of the ATCo mental models. Researchers generally agree on spatial aspects in the ATCo mental models. Many researchers tested multidimensional scaling techniques, data visualization method regarding similarities of individual objects or data points, to ATCos to explore the existence of spatial aspects on their cognitive process [116, 117]. Landis et al., 1967 concluded that mental models of ATCo have spatial characteristics and results from Lapin, 1982 showed the experts have a three-dimensional spatial characteristic in their pictures.

Researchers generally agree that there is a difference between the mental models of novices and experts in quality wise. Mogford, 1990 conducted a recalling test to ATCos and concluded that recalling ability is related to their quality of mental model because results showed a positive correlation between recalling and their radar reading ability [109]. With other related studies , this result can be the evidence that having a higher quality level of the mental model helps the practitioner's task performance. Also, Vincente, 1988 stated that amount of information that an operator can remember and recall is also the critical ability and it affects his/her cognitive process because of clarity and fruitfulness of knowledge he/she has [118].

D.3.3 Prescribed Models of ATCo Actions

Radio Technical Commission for Aeronautics (RTCA), a private organization developing aviation standards, adopted the concept of prescribed modeling to the field. In 1975, RTCA issued the minimum performance standards for ground proximity warning equipment and standardized executions of pull up maneuvers against conflict with terrain [119]. The actual application of the prescribed models started in 1990 to provide conflict resolution maneuvers for the runways [120].

Besides its primary usage, researchers started utilizing the method in many ways for the air traffic studies. The two most frequent applications are on model assumptions and operator training materials. From the early stage of modeling conflict resolution methods, researchers utilize the prescribed models in their tools to provide fixed maneuvers in certain situations. It often presented as assumptions of the models. Waller & Scanlon and Carpenter & Kuchar applied a prescribed climbing maneuver for the conflicts in the airport areas [121,122]. Also, researchers embedded the prescribed models in the mathematical ones. If an aircraft conflict resolution model only able to generate horizontal maneuvering solutions, we can understand it as (in systematic perspective) its structure of resolution generation has a prescribed step categorize all input conflict as problems that can be solved by a maneuvering option. In these cases, the prescribed methods do not play significant roles in the models. However, it shows that other types of models possess some aspects of the prescribed modeling.

Another popular usage is on developing operator training materials. Handbooks and manuals including Air Traffic Control Handbook from FAA are the best examples. These works include prescribed protocols explaining what an operator must perform in certain situations. For example, the ATCo handbook sequentially lists the tasks for clearance of an aircraft to take-off. The models are handy in training both human and computer operators because they can reduce a significant amount of time on deciding what to do. If an aircraft conflict resolution can provide either horizontal or vertical maneuvering solutions, it should compare which maneuvering option is better. A prescribed model does not need this process, so it will reduce total computation time to half right away by removing one option. In simple words, the prescribed models are methods to trigger predefined procedures. Chief functions in the model take input and make conditional judgments based on the information in the input. This information may possess more than one factor. For example, both conditions of runways and aircraft status trigger the predefined maneuver from Waller & Scanlon and Carpenter & Kuchar. When the functions make decisions, they evaluate whether the factors satisfy their conditions. The functions in Waller & Scanlon and Carpenter & Kuchar models are checking whether an aircraft is climbing or not and whether there is a parallel runway approach. Studies like Prandini et al. 2000 show how prescribed models trigger their mathematical functions [123]. We can find a more direct use of the predefined models from the Tactical Separation Assisted Flight Environment (TSAFE). TSAFE is a backup system of a primary-automated conflict resolver to provide immediate maneuver options for a predicted loss of separation within 2 minutes [124]. Since the system is designed to provide a solution in a short time, it processes a predefined set of procedures to check which maneuvering option is better than others [125]. As the input and evaluations are multi-dimensions, a function should have at least two outputs; one for the input satisfied its standards and vice versa. The output can be a final output of the model or input to another function. Thus, we can also put the functions in series to build a sophisticated structure for various output. State, knowledge, agent, and protocol-based models are well-known examples of the prescribed models with the sophisticated functions.

State-based models utilize prescribed modeling method to identify the current state of its target. Landry, 2012 introduced a state-based model that can track the current state of aircraft [126, 127]. In the model, predefined states of aircraft exist, and multiple evaluation functions check the status of aircraft to make decisions. Also, the state transits to other ones if a particular time is passed or event occurs. Knowledge-based models are simpler versions of artificial intelligence. The models provide solutions based on its knowledge or store solutions. Ezberger, 1995 emphasizes benefits from knowledge-based functions on the air traffic control system [128]. Later studies introduced its application powered by decision tree methods [129, 130]. In short, the models go through logical procedures to make traffic control decisions. For more accurate output, they require a significant amount of information beforehand. Agent-based models consider each object in a simulation environment as independent and self-oriented. The agent has a predefined set of actions that can be triggered by various inner or outer factors. Since agents behave independently to pursue their goals (processing a set of predefined procedures), they create emergent behaviors. For air traffic control, agents, aircraft, and ATCoS must cooperate with each other to achieve their goals and researchers study how they work together to resolve conflicts [131–134]. On the other side, researchers used the method due to its characteristics regarding independence. They applied the concept of free flight on the agent-based modeling to evaluate decentralized air traffic control systems [18,135,136].

Prescribed models have two critical deficiencies. They are coming from the characteristics of functions that generate predefined output. Fundamentally, their functions do not create solutions, they evaluate the situation and only able to one of the elements in the predefined set of items. Because of this structure, the prescribed models possess limitations in quality of output, the flexibility of the models, and depth in situation awareness.

The set of solutions is hard to be very specific and detailed. Conflict resolution maneuver is a complicated decision. If there is a conflict between two aircraft, ATCo must decide which aircraft to deviate from its nominal route and how. Since solutions are predefined, it is not so difficult to decide which aircraft to alter and which maneuver option to apply. However, how much to alter is very subjective and case-specific factor. ATCo maneuver is not just asking an aircraft to climb up or down, and it can also be altering next waypoint to somewhere else so that the aircraft needs to change its heading. Moreover, a specific maneuvering option and context are subject to change if the environment changes due to weather or other aircraft. Thus, it is challenging to prepare a master set of solutions that have all possible solutions. Itan is a standard issue of the prescribed models. For example, Waller & Scanlon and Carpenter & Kuchar's predefined models only able to provide resolution maneuver with fixed climbing and turning angle. The prescribed models are more suitable to narrow down a solution pool.

Since there are limitations on the output variation, situations a model can resolve is limited. Their functions lack flexibility because one function can only provide a solution for one type of cases. So, the models become case specific. If a model wants to cover many situations, it requires at least that many functions in it. However, it is challenging to collect all possible conflict situations and categorize them into some instances. The method is useful when its target system is simple. However, the current air transportation system is sophisticated than in earlier years, and it will add more complexity to the next generation. Thus, it will be challenging to conduct aircraft conflict resolution tool solely with prescribed models.

The performances of prescribed models are highly dependent on input factor evaluation processes. Intuitively, a case-specific solution only works for the corresponding case, and we can provide a case-specific solution only when we know the problem belongs to that case. If the chosen factors are misleading, the models will offer unrelated solutions, which will lead to failure of the traffic control system. Thus, determining a set of input factors that present a case is the critical procedure during the development of the model. This procedure should include a step to prove that the chosen factors can represent the case effectively along with identifying their candidates. The proof itself is another complicated problem because it will require some amount of empirical or theoretical work that is not defined.

D.4 Mathematical Studies of ATCo Actions

Researchers approach mathematically to construct automated conflict detectors and resolvers. Since the 1990s, aircraft equip the traffic collision avoidance system (TCAS), which monitors airspace around an aircraft to identify active transponder-equipped objects such as other aircraft. Based on received signals, TCAS automatically calculates the status of other aircraft (climbing or descending). From the 1980s, as technologies and concepts of TCAS established, researchers also seek to develop mathematical models and many types of research published after 1990. In one way, the optimal conflict resolution can be considered as extending the concept of TCAS to not only identifying potential threats to an aircraft, but also provide remedies to avoid any conflict. As demand and volume of the air traffic increases, interest on improving its control systems also grown together.

Formulation of mathematical conflict resolution models generally follows the process described below. First, a practitioner constructs a set of equations to describe the conflicts. This set of equations includes an objective such as what kinds of factors to consider in a model and what to minimize or maximize. Also, equations have variables that reflect factors or conditions. For example, this phase includes implementing the dynamics of aircraft such as its movement. Intuitively, as the number of equations and variable increase, the model becomes more complicated and may reflect more details regarding the conflicts. Second, a practitioner chooses an algorithm to solve the set of equations. Some algorithms must be modified to fit due to its fundamental structure that was designed for other problems. Sometimes a practitioner first comes up with a solver than formulating a set of equations that will fit the algorithm. Third, a practitioner tests a model by simulating aircraft conflict cases applying scenarios or actual flight data.

Objectives of the optimal conflict resolution models are simple and straightforward: to avoid aircraft conflicts. However, the researchers took various direction to achieve the goal. Also, there are many ways to categorize the studies. This section synthesizes those categories. The first subsection describes how the researchers frame the aircraft conflicts. Then, the following subsections list mathematical variations such as algorithm types, constraints, and variables.

The most obvious factor to categorize the studies is a flight condition. There are two different types of conditions considered in the studies; nominal (controlled) and free flights. In nominal condition, two assumptions are widely used. First, the studies assume that air traffic controllers are responsible for the maneuvers just like the conventional air traffic control operations. Thus, most studies consider the nominal condition and focus on the separation assurance. Second, aircraft have deterministic movements. Studies assume all flights have their predefined flight trajectories and strictly follow theirs. Thus, there is no uncertainty in movements of aircraft unless specific execution is given to avoid any conflict. With this assumption, studies predict and detect conflicts conveniently.

Other researchers envision the free flight in the future with technologies to support it. In this case, ATCos do not control flights and pilots are responsible for the separation assurance. Since aircraft can fly freely, there are no predefined trajectories, which creates uncertainties in aircraft behaviors. It makes the predictions to be challenging. For example, an aircraft can encounter unexpected conflict due to sudden changes from other aircraft. Thus, a model should monitor movements of each aircraft very closely with a short time interval for the accuracy of prediction. Also, the accuracy of conflict prediction is relatively lower than the nominal condition and more complicated and requires more computations to detect them. Due to these characteristics, a solution for conflict may continuously change as a circumstance change.

Another critical factor to consider is how to frame the problem. Based on the reviewed literature, there are two different ways to define the aircraft conflict: subjective and objective point of view. In a straightforward case, aircraft conflict occurs when there is a pair of aircraft that will lose separation or even collide in the future due to their current statuses such as heading, airspeed, and altitude. From a subjective point of view, other aircraft become objects that one aircraft should avoid. Thus, other aircraft are considered as obstacles or even considered as threats to an aircraft. Also, not only aircraft but also weather and landscapes are also considered as obstacles. In this type of perspective, an aircraft must find its way out from any dangerous circumstances. Thus, the model cannot control the obstacles, and only a target aircraft make maneuvers against them. The objective point of view takes precisely the opposite approach. It considers a conflict as one event itself to solve, which means all objects included in the situation must cooperate to find a solution. Depends on the method, a model selects the best resolution to either aircraft in a conflict or model performance regarding its objective. So one solution may require a maneuver for an aircraft while another one requires maneuvers for multiple aircraft.

State of the conflicts considered in the studies is another critical standard. The models apply to either one of the two states: nominal and close quarter conflicts. Nominal conflicts are predicted conflicts that may cause a LOS or collision with reasonable time to respond and the close quarter ones are cases without enough time. Most mathematical models ensure separation for the nominal conflicts. In the current air traffic management operations, ATCos manage conflicts in this state daily, and the primary purpose of their actions are avoiding overlaps of aircraft's safety zones by assuming all aircraft move as intended. Thus, models designed for the nominal conflicts aims for providing conflict resolution recommendations to ATCos or even replacing their task. Opposite to the nominal state, there are models focused on the resolutions for close quarter cases, which have a closer relationship with the concept of TCAS. Some models include resolution algorithms for both cases.

Among many mathematical approaches, most researchers adapted optimization methods. Optimization has benefits compared to other mathematical methods. All mathematical approaches can provide conflict resolutions. Unlike others, optimization models generate multiple solutions and choose the best one based on their objective functions. The goal of objective functions is either maximize or minimize some performances. To utilize this characteristic, researchers construct cost metrics and guide their models to provide results that are guaranteed to spend minimum cost. For air traffic management, the most critical cost metric is the safety of aircraft. Safety can be interpreted in many ways, but typically it is considered as a separation between aircraft. Besides the safety, researchers consider other cost metrics such as fuel consumption, total travel time, deviation from the original trajectory, and even workload of operators. After researchers determine a set of the objectives, they quantify the objectives into a series of variables and constants. Then, they decide what kind of constraints should be considered in the model. The variables used for the objective function must be included in the constraints to narrow down possible solutions. After the model is completed, researchers compute the objective function and constraints together to find a solution that satisfies all conditions.

Researchers determine specific algorithms to apply in the optimization models based on how to formulate the models. Geometric algorithms are the most common methods for the air traffic conflict. Fundamentally, aircraft conflicts are a geometric problem, because two or more objects are expected to be at the same location at the same time. Thus, this approach is one of the simplest and the most straightforward methods. This method focuses on geometric deviations from the nominal trajectory of aircraft. Most studies adapted this approach utilizes velocity vectors of aircraft to measure the deviations, and their accuracy and realism depend on the other constraints to define movements of aircraft and their surroundings [21,137–152]. Additionally, due to the characteristics coming from the movements, a structure of optimization models are non-linear functions. While some models took a fundamental and straightforward approach with geometric algorithms for the separations, others consider performance metrics such as the economic cost of taking specific maneuvers to aircraft. When the objective function becomes more complicated, researchers apply techniques such as game theory or genetic algorithms to find solutions [146, 152]. Listed techniques are widely used in economics and operation research area. Game theory provides gains and losses on conflict resolutions, which enables practitioners to make mixed strategies (mixed solution consists of a win for one objective and vice versa) for an improvement in overall performance. Genetic algorithms find better solutions from a pool of solutions during the iterative process. So, the algorithms take multiple iterations until they find the best solution or whether the iteration is exhausted.

A stochastic approach is another common mathematical method. The fundamental reason for utilizing a stochastic approach is accounting uncertainties in aircraft movements. Even if aircraft should follow its flight plan or nominal trajectory, it is always possible that there is a probability that it will not. Also, even if we consider an aircraft is following its path, there are always small deviations due to many factors such as error tolerance from sensors equipped in aircraft or radars. Unlike optimization models, this type of models does not have objective functions. However, their algorithms always choose the safest solution: having the least amount of chance to have a collision. This approach is more suitable for making sudden maneuvers to avoid unexpected situations. Stochastic models predict the worst-case scenarios, which the most dangerous movements that other objects can take against an aircraft [153–157]. Based on the predicted movements and probabilities to take those actions, the models construct solutions that will avoid the threats. If it is impossible to avoid the threats, models will choose solutions that will take the least amount of risk. Due to these characteristics, stochastic approaches are more suitable to close quarter situations where an aircraft must make dramatic maneuvers to react to unexpected situations such as aircraft in close distances. Other studies implemented stochastic models for free flight conditions due to its capability to handle uncertainties in movements of objects.

The optimization and stochastic models are essential approaches to finding aircraft conflict resolutions. However, other mathematical models are approaching with an entirely different point of view. Force-field models are one of them. The method is initially developed for robots to reach their goals without colliding to surrounded obstacles. All objects in this method have two different characteristics like magnets; attractive and repulsive forces. Objects have an attractive force toward their goals, so they want to keep moving toward the goals. At the same time, they have a repulsive force against other objects so that they can always be located certain distances apart from others. Since the method was initially developed for the robots on the ground, researchers modified to fit into the air traffic. Original methods only consider one robot at a time, and a robot deals with its obstacles one by one. Also, the obstacles do not necessarily move. Aircraft conflicts are more complicated than this case: not only objects are moving at high speed, but also conflicts are not always one to one situations. Researchers took three different directions by prioritizing aircraft to reflect the characteristics of air traffic [158–165]. Global prioritization set priorities to all other aircraft in its environment [158, 159, 162–165]. If there are higher and lower priority ones to consider at a time, a model ignores lower ones. The order of priority can be set in many ways, and it is recommended to re-order periodically. Opposite to the previous method, local prioritization set pairwise priority orders based on a geometry of nearby aircraft [161]. Thus, as an aircraft moves, objects in the search range of aircraft change and their priority also changes as their distances to the aircraft. Local coordination takes a little bit different approach compared to the two previous methods. Instead of labeling priority orders on objects regarding a subjective point of view, each object only deals with others that are threatening [160].

Instead of purely focusing on mathematical functions, some studies took a slightly different path: heuristic approaches. Knowledge-based studies utilize mathematical functions to understand a problem and pick a proper knowledge and how to apply it [166]. Before this process, the method should obtain solutions and how to categorize them affect its performance critically. Another heuristic method is agent-based modeling. This method focuses on the interaction among different agents (aircraft and ATCos). Each agent has their preferences, and they must work together to find a solution that everyone satisfies [167, 168]. If there is a conflict, the model generates a solution and provide it to aircraft involved in the case. They decide whether they agree with it or not depending on their preferences and constraints. If there is a rejection, the model modifies the solution to meet the requirements of the agent who rejected the previous one. This process iterates until everyone agrees.

Along with the algorithms to compute aircraft conflict resolutions, accuracy and performance of mathematical models are critically dependent on factors considered in the computations. Researchers translate the factors of the air traffic into variables in their models and utilize them to form constraints. These factors include any information about aircraft, surroundings, and the structure of the air traffic system.

Dynamics and physics of aircraft are one of the most crucial factors in the models. Dynamics include specifications of aircraft such as type, size, weight, minimum and maximum airspeed, power, etc. Physics include the motion of aircraft such as effects of a heading angle, descending, and ascending. These factors govern whether an aircraft in a model can behave realistically. If a model does not reflect physics of aircraft, conflict resolutions may include radical movements that an aircraft cannot follow. Also, ignoring some factors will generate resolutions that an aircraft can follow, but the operator will not execute due to other reasons such as the safety of passengers. Unlike the physics, some studies ignore the dynamics and assume that all aircraft have identical specifications to only focus on maneuvering matters.

Many studies adopt rules of the current air traffic management system. For example, studies reflect aspects of operators so that the models deal with conflicts in a sequential order that is determined by the severity of the cases often calculated by a distance between two aircraft and time left before the loss of separation. Also, choosing a resolution that satisfies objective functions and constraints among varies solutions also can be considered as mimicking decision making a process of air traffic controllers despite the mechanism of generating the solutions. If the studies focus on avoiding a LOS among aircraft, they implemented the concept of the safety zone that the current system utilizes to determine aircraft conflicts. Also, studies are extending this concept to have their safety regions.

Primarily, mathematical conflict resolution models include variables to represent at least two objects, aircraft in most cases, in a conflict. Complicated models have multiple aircraft that not only have multiple conflict pairs but also conflicts caused by multiple aircraft. With aircraft, there are studies include other types of objects in their models. To make the models more realistic, some studies adapted weather changes in their simulation environment. Abnormal weathers such as a storm are considered as a large-size obstacle to avoid if they appear on the nominal trajectory or new one to avoid the conflicts. Another type is immobile objects such as featured terrain. If an aircraft should fly at a low altitude, tall buildings and telegraph towers become obstacles.

Mathematical aircraft conflict resolution models put constraints on aircraft movements other than considering the physics of aircraft. Studies divide aircraft movements horizontally or vertically. In horizontal trajectory models, studies assume that aircraft fly at the same altitude and vice versa. Thus, there is either horizontal or vertical maneuvers exist depending on this constraint. There are studies considering both horizontal and vertical maneuvers. Early studies tend to consider only one type of maneuvers (more horizontal maneuvers) and recent studies deal with both maneuvers at the same time.

Researchers build simulations to test the performances of their mathematical conflict resolution models. The simulations require input data to test the performances, which should reflect air traffic conflicts. Depend on how a model takes specific factors and what is required to generate output, each study includes different characteristics and factors in their input data. For example, it includes the size and complexity of air traffic situations in the input. With the output, researchers analyze them in many ways. Especially for optimization models, researchers validate the results to check whether the solutions are optimal regarding their objective functions and constraints.

The most apparent standard to categorize the experiments is a type of the air traffic conflicts considered in the simulations. Commonly, we divide them into a conflict caused by a pair of aircraft or multiple of them (global conflict). Typically, mathematical models are only able to resolve a conflict of one pair of aircraft at a time. To resolve global conflict, those models resolve conflicts of any two aircraft in the situation until every aircraft is safe. Also, conflicts do not only consider aircraft. There are experiments testing conflicts between aircraft and other obstacles and multiple aircraft with other types of obstacles such as weather conditions.

The number of aircraft in the input is another category. To generate resolutions for aircraft conflicts, experiments need at least two aircraft. However, there are studies with single aircraft that focus on avoiding other types of objects. Also, a large number of aircraft in input does not necessarily mean it includes that much of conflicts.

Besides factors related to the conflicts, behaviors of aircraft in the input is another critical characteristic. All aircraft in the input are moving objects, and the input deterministically or stochastically controls their movements. Deterministic input has perfect information of aircraft and aircraft move as written. Thus, models already know how aircraft will behave. Stochastic movements are more dynamic. Aircraft move freely within given boundaries. It makes models to have difficulties in predicting the future. Generally, models designed for free flight and close-quarter conflicts implement stochastic input for their simulation.

The last category to discuss is the origins of the input. There are two different sources on the aircraft movements. Majority of studies generated their flight trajectory data. It can be as simple as two identical aircraft moving straight forward in same airspeed and altitude and toward each other. Some studies put more details and variations to the trajectories to give complexity to the input. Only a small portion of studies implemented actual flight data. Intuitively, generating input scenarios are convenient in many ways then applying real-world ones. However, in earlier studies, it was very challenging to obtain the real data due to their accessibility to the public.

Results of experiments vary by the type of mathematical approaches. Optimization models provide the conflict resolutions, and they are optimal regarding their definitions and setups. However, other types of mathematical approaches not always generate ideal solutions. Since probabilities highly govern stochastic models, it is impossible to have 100% safe resolution, and it gets more challenging as the conflict situation becomes more complicated. In force field approaches, sometimes aircraft are in steady states. Due to directions of recursive forces from other objects, some aircraft cannot find a way out, and they stop moving.

Not only each study but also the mathematical approach itself have shortcomings. This section focuses on addressing limitations of the studies regarding their applicability to the air transportation system because the goal of studies is developing aircraft conflict resolution tool for the system. Also, this section only focuses on limitations of the mathematical models without comparisons between other types of methods.

One of the essential characteristics of the aircraft conflict resolution models is they are intended to resolve real-world problems. In general, if a solution to a problem is provided without fully understanding a problem is highly doubtable, and a similar situation is occurring from the mathematical models. The models solve aircraft conflict resolutions in their ways. As constraints, they reflect some realities in the models, but it is limited, and the level of reflection varies. For example, one model ignores dynamics or aircraft while another model ignores their physics. Some results show very radical and complicated movements that wither pilot nor ATCo will accept. Moreover, some models utilize strong assumptions such as the same airspeed or altitude. At this point, we do not know what is the right amount of information that must be included in the mathematical models. However, it does not mean we can punch in some numbers to a calculator and see if it can give us an output. Unfortunately, most studies only focus on whether some mathematical algorithms can solve this type of problem.

Another deficiency of the mathematical models, specifically optimization models, is in the characteristics of their solutions. Mathematical solutions lack flexibility. Researchers programmed these models to follow and satisfy objective functions and constraints strictly. Often the objective functions are minimizing deviations from the nominal trajectory. To avoid conflict and minimize the deviation, the models must choose a route that each aircraft pass each other very carefully. In some studies, the distance is the safety zone and even shorter than that. The studies generate these solutions in scenarios where there are not many aircraft present at a time. The solutions are mathematically correct, but we need to consider whether it is operationally the best answer carefully. If we have plenty of airspace for aircraft in a conflict, taking the risk of putting two aircraft close to each other maybe not the best answer. Also, the optimization models require perfect information to generate solutions. If one aircraft or one factor considered in a model does not behave as it should, the solution becomes useless. In the real world, things do not happen as they should.

One of the reasons why the studies limited their experiments with the small number of aircraft and making strong assumptions is due to computational difficulties. Computational difficulty increases exceedingly as the mathematical models become more complicated. The complexity increases only when the models reflect more aspects of the problem. Moreover, many studies do not state how long it takes to generate solutions. The computation time is essential in this case because if we want to utilize mathematical aircraft conflict resolution models to the real-world, response time becomes the most critical factor.

The last point to discuss is problems that appear if we adopt the mathematical resolution models to the air traffic management system. As stated previously, the primary purpose of the studies is developing a decision supporting tool for ATCos. The studies only consider mathematical perspectives, which means their algorithms do not consider how ATCos resolved conflicts so far. An immediate problem will arise if we apply the models to the current system. The models will generate solutions, but we do not know whether ATCos will understand the solutions and accept them. Moreover, to make ATCos understand the solutions, they must fully understand how the algorithms work and why they make such decisions. It will create a severe conflict between the tools and operators, and it will affect the system negatively. For example, if ATCo does not understand or agree with decisions from the models, ATCo must take additional steps such as trying to understand the solution from the models or reconsider his/her decision. It will take a longer time than the current system where ATCos make decisions and execute them.

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