Trajectory Based Operations Conflict Resolution Advisories: Fast-Time Simulation Study Investigating Benefits from Improved Intent Entry

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16. Abstract

This technical note documents a fast-time simulation study for the Conflict Resolution Advisories (CRA) Voice and Datacomm project specified in the NextGen Project Level Agreement (PLA) for FY2010. The study investigates the benefits of improved intent entry. Five levels of intent entry were simulated using two predicted future traffic levels (2018 and 2025) and five different Air Route Traffic Control Centers (ARTCC): Chicago (ZAU), Denver (ZDV), Los Angeles (ZLA), Miami (ZMA), and New York (ZNY). In total, 50 simulation runs were modeled. Various system performance metrics were examined and experimental design techniques applied to estimate the benefits associated with "closed clearances" from CRA, resulting in improved entry of intent to the ground automation system. This technical report documents an extensive methodology of simulation modeling and synthesis of results using experimental design techniques and provides a detailed examination of the effects of intent entry.

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Executive Summary

An advanced separation management function called Conflict Resolution Advisories (CRA) is a crucial piece of the planned implementation of the Federal Aviation Administration's (FAA) Next Generation Air Transportation System (NextGen). CRA is a capability designed to aid the air traffic controller in ensuring safe separation in air traffic. It uses the En Route Automation Modernization's (ERAM) conflict probe algorithm to detect potential separation violations and provides a rank-ordered listing of potential conflict resolution maneuvers. The resolutions are presented to the controller via advanced menus accessible from the flight data block on the radar console. CRA allows the controller to insert their selected resolution into the ground automation system.

In the current system, a controller's conflict resolutions are frequently issued via voice and are often unknown to the ground automation system. A key benefit of CRA is that it facilitates the entry of full 2-part amendments (e.g., including the second part of a 2-leg lateral maneuver or next altitude transition point). The authors hypothesize that improved intent entry leads to improved performance of the ground automation with respect to trajectory modeling and conflict alert generation. This paper documents a study testing this hypothesis, in support of the cost benefit case for CRA.

The study employs experimental design techniques to plan and synthesize the results of 50 simulation runs. Several factors are examined including forecasted traffic demands from years 2018 and 2025, five airspace centers, and a parameter to reflect the level of intent entry to the ground automation system. These years are chosen because they represent the mid- and far-term time frame for NextGen, and five centers are selected to reflect the breadth of traffic characteristics in the National Airspace System. Metrics of interest in this study are trajectory accuracy and alert performance, which the FAA's Concept Analysis Branch (ANG-C41) Conflict Probe Assessment Team has considerable experience in evaluating. Simulation runs are made using the Java En Route Development Initiative (JEDI) modeling environment and Problem Analysis Resolution and Ranking (PARR) software. PARR is the CRA prototype software developed by the MITRE Corporation's Center for Advanced Aviation System Development and has been assessed in several experiments with Certified Professional Controllers (CPC) from across the country. Experimental models are fit to the results, and analysis results are presented in detail in this report.

Overall, a performance improvement is observed in both trajectory modeling and conflict probe alerts with increasing levels of intent entry. Almost 45,000 flights over 240 hours are simulated and the output data is fit to a statistical model. The model fits the data closely, capturing between 97 and 100% of the variation in the data for different response variables, and indicates a strong non-linear effect from the parameter that reflects how completely controller intent is entered to the ground automation- the size of the effect is highest at lower levels of intent entry. The results indicate a potential improvement in trajectory modeling: 61% decrease in the overall average horizontal error (the two-dimensional distance between a sampled trajectory point and the time-coincident track point) and 42% decrease in the overall average vertical error when comparing scenarios that simulated the least amount of controller intent entry to scenarios with complete entry of full clearances. In addition, the number of trajectories generated that do not coincide with a flight plan amendment decrease by 42% overall between these scenarios, indicating that the trajectories generated are more stable and that less reconformance rebuilds are necessary with more complete entry of a controller's future intent.

These improvements in trajectory prediction and more accurate trajectories lead to better performance of the conflict probe. Two metrics that are used to demonstrate conflict alert performance are the first quartile of predicted warning time, and the count of alerts with duration greater than one minute.

Inaccurate trajectories result in an increase in late notification of alerts -in other words short warning time before a conflict. The authors consider the distribution of predicted warning time, or difference between predicted conflict start time and first time of notification for each conflict. The first quartile (25th percentile) of the predicted warning times of the alerts in seconds is a valuable metric to describe how the lower tail of the distribution is affected. From the statistical model, the first quartile of predicted warning time increases by 58 seconds overall when increasing full entry of 2-part clearances to the ground automation from 0 to 100%. The count of alerts with duration greater than one minute is important because with missing intent, some alerts will not be removed upon issuing an amendment. Alerts that are not deleted at the time an amendment is entered can be identified in this study by an alert duration greater than one minute, and represent problematic events. The count of these alerts decreases by an average of 80% over all experimental runs when increasing full entry of 2-part clearances from 0 through 100%.

This study presents a comprehensive simulation of improved intent entry and evaluates the impact that Conflict Resolution Advisories could have on the performance of the ground automation with respect to trajectory modeling and conflict alert generation. The authors employed metrics that reflect important performance aspects of trajectory modeling and conflict probe alerting. The results indicate a significant impact and definite trend of performance improvement with increasing entry of full 2-part clearances, which the use of CRA facilitates.

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1. Introduction

This Federal Aviation Administration (FAA) technical note documents a study identified in the NextGen Project Level Agreement (PLA) titled *TBO - Conflict Resolution Advisories - Voice and Datacomm* [6], where TBO is the acronym for Trajectory Based Operations. The project includes the concept analysis, prototyping, and software development activities required to implement automated resolution advisories for predicted conflicts. This report documents the second major fast-time simulation study for the Conflict Resolution Advisories (CRA) project and is intended to support the cost benefit case for CRA. The study will generate simulated data from a designed experiment and use the data to quantify a benefit of CRA, namely, improved entry of aircraft intent. This introductory section presents the scope of this document, a brief background of the study, the benefits to be studied, contributors, and the organization of the document.

1.1 Scope of the Document

This document describes a fast-time simulation study that supports the PLA titled, *TBO - Conflict Resolution Advisories - Voice and Datacomm* [6]. This study provides a benefit analysis comparing the current procedures for resolving aircraft-to-aircraft conflicts, in which the ground automation may not be completely furnished with future intent information, with procedures envisioned for future use. These future procedures will make it easier for controllers to issue clearances that contribute to a "closed-loop" system[1] in which the ground automation system is provided with future intent and can in turn generate more accurate conflict probe results and recommended resolutions.

1.2 Background

The FAA created the National Airspace System (NAS) to provide a safe and efficient airspace environment for the air transportation system in the United States. This includes all commercial, general civilian and military aviation. The NAS is composed of a network of air navigation facilities, air traffic control facilities, and airports, along with the technologies and the rules and regulations to operate the system. As the air transportation system in the United States has grown, the NAS has evolved by incorporating new procedures and new technologies.

The Joint Planning and Development Office (JPDO) has established a vision for the Next Generation Air Transportation System (NextGen)[4-5] to fulfill its mission to design and deploy an air transportation system meeting the nation's anticipated needs in 2025. Trajectory Based Operations (TBO) is an integral part of NextGen and represents a paradigm shift from today's mainly tactical air traffic control to strategic trajectory-based air traffic control that utilizes an unambiguous path in space and time. NextGen addresses a number of operational improvements organized into solution sets of related capabilities. CRA belongs to the NextGen TBO Solution Set.

CRA is an advanced decision support tool (DST) designed to aid controllers in formulating more efficient resolution maneuvers. It is ground-based and implemented into the En Route Automation Modernization (ERAM) system. CRA will provide a rank-ordered listing of potential conflict resolution maneuvers and

---

1 A clearance issued with automation supporting a "closed-loop" system translates to aircraft maneuvers that are directed by air traffic control, like today, but unlike today the automation both anticipates the future components of the maneuver and provides advisories on what they are. This is contrasted to "open-loop" clearances that are issued today that may or may not be entered into the automation, and even when entered, later components of the maneuvers are unknown to the automation.

is expected to improve operational efficiencies as well as increase the use of "closed-loop" clearances where future controller intent is fully known to the ground automation system.

1.3 Benefit to be Studied

The fast-time simulation described in this study plan is a part of a larger study defined in the PLA [6]. This effort is further clarified in the *TBO - Conflict Resolution Advisories Benefits Plan* [7]. In these documents seven anticipated benefits from implementing CRA were identified:

- **Benefit B1: Reduced delays due to increased sector capacity**
- **Benefit B2: Reduced maneuvering due to improved intent entry**
- **Benefit B3: Reduced maneuvering due to more strategic controller actions**,
- **Benefit B4: Reduced altitude restrictions**
- **Benefit B5: Reduced number of altitude capped flights**
- **Benefit B6: Reduced use of altitude for direction of flight (DOF)**
- **Benefit B7: Increased use of established direct routes between city pairs**.

The study described in this technical note uses a fast-time simulation tool to investigate Benefit B2: Reduced maneuvering due to improved intent entry. This definition is expanded to include improvements in trajectory modeling and conflict probe alert performance. The benefit from improved intent entry is associated with the use of 2-part maneuvers. CRA menus support the entry of 2-part step climbs and descents and 2-leg lateral maneuvers, and it is anticipated that the introduction of CRA will increase the frequency and accuracy of controller intent entry for these types of resolutions.

In the current system, controllers often issue off-route headings without amending an aircraft's flight plan [10]. This leaves the automation with no information on the controller's intent to return the aircraft to route; the trajectory modeler must assume a future maneuver turn point. Similarly, controllers may issue temporary altitudes during climbs [10]. Even though the temporary altitude may be entered into the automation, the intention of the controller regarding planned resumption of the climb is not, and the expected time the aircraft will remain at the temporary altitude must be assumed by the trajectory modeler. In cases such as these where future intent is not entered into the ground automation, the flight path intent known to the ground automation has limited accuracy. The trajectories generated without the benefit of correct intent have increased potential for false and missed alerts, alert instability, and increased controller workload.

CRA will reduce the entry of open clearances such as temporary altitudes and off-route headings in favor of full 2-part clearance entry. When a 2-part maneuver is selected and issued to an aircraft from a CRA menu, the entire maneuver is included as a change to the known intended flight path in the ground automation. This updated intent information is incorporated in trajectory predictions used for conflict detection. This "improved intent entry" to the ground automation is anticipated to have positive impact in reducing trajectory modeling error and the number of re-conformances, as well as improving the performance of conflict probe alerts in terms of false alerts, late alerts, and other qualities that affect controller workload.

A qualitative assessment of the benefit from CRA related to improved intent entry is detailed in a report by Kuo and Idris [13]. The report notes that "the un-ambiguous identification of aircraft intent is essential for accurate trajectory predictions, thereby allowing accurate and reliable alerting decisions at the conflict detection and resolution stages." To support this idea, Kuo and Idris present various air traffic scenarios to demonstrate how improved intent entry in CRA can result in safety benefits. This is accomplished by constructing benefit mechanisms that connect intent entry to operational errors.

Besides illustrating the safety mechanisms discussed above from [16], the simulation study documented in this report will quantify the potential improvement to the trajectory and conflict probe predictions resulting from the capture of the additional intent that the CRA tool provides the ERAM automation.

1.4 Contributors

Several organizations are involved in the CRA project. Three groups that assist in this particular study and their roles are mentioned here.

The FAA Concept Analysis Branch (ANG-C41) is located at the William J. Hughes Technical Center, Atlantic City International Airport, NJ. ANG-C41 has experience in designing and conducting simulation-based studies and is supported on-site by CSSI, Inc and General Dynamics Information Technology for this project. The FAA team is responsible for implementing the project plan documented in [19] including experimental design, preparing input files, performing output data analysis utilizing specialized tools, and documenting the results.

The MITRE Corporation's Center for Advanced Aviation System Development (MITRE-CAASD) is supporting all aspects of the study and providing the prototype CRA software inside their en route research prototype, Java En route Development Initiative (JEDI), to simulate various scenarios in fast-time and produce output data for analysis.

Engility, formerly L-3 Communications Corporation, is addressing the benefit mechanisms and assisting in documenting flight examples.

1.5 Document Organization

This technical note is organized in the following sections. Section 2 describes the approach and methodology of the study including the research hypothesis, overall approach, experimental design and model, fast-time simulation software, data preparation, and analysis tools. Section 3 presents the results in four sub-sections for trajectory modeling and conflict alert performance, the statistical model, and flight examples. The study's conclusions and recommendations are found in Section 4. Section 5 provides a glossary of related acronyms. Section 6 contains the references cited within this document. Finally, supplemental appendices contain various supporting tables and figures.

2. Study Approach

This section describes the experiment implemented in order to study the benefit from improved intent entry. The research hypothesis is stated, the overall approach and design of the experiment to answer this hypothesis is presented, simulation methodology and data preparation steps are detailed, and relevant metrics are discussed.

2.1 Research Hypothesis

The objective of this study is to quantify the benefit of the ground automation having the correct intended flight path for the entire maneuver when issuing 2-part maneuvers and test the significance of any impact. To this end, the simulation and analysis is designed to determine if the automation's performance improves or degrades with increased entry of controller intent. Specific levels of intent entry are modeled by randomly withholding (to the desired degree) full amendment clearance information from the ground automation; this methodology is detailed in Section 2.5. The null hypothesis to test the impact of increased levels of intent entry in this study is stated as follows:

> *Regardless of the en route air traffic control center and future forecasted traffic level, increasing the percent of amendment clearances provided to the ground automation (i.e. intent level) does not yield improved performance metrics.*

If the null hypothesis can be rejected with a high level of confidence, this strongly implies that there is a positive impact from increasing intent levels, as stated by the alternative hypothesis:

> *Increasing the percent of amendment clearances provided to the ground automation does improve the performance, as indicated by the same metrics, at different en route centers and forecasted traffic levels.*

The metrics used in the analysis to capture performance are related to trajectory and conflict probe accuracy and are discussed in detail in Section 2.7.

2.2 Overall Approach

As stated in Section 1.3 this study addresses benefit B2 as identified in the PLA [6] and summarized in the CRA Benefits Plan [7]. The assessment of this benefit was quantified using controlled experimentation techniques based on experimental design principles. The data required to assess these benefits was gathered using a fast-time simulation of the NAS. Figure 1 presents a graphic depicting the NAS as a process that is to be analyzed in this study, including the inputs and outputs.

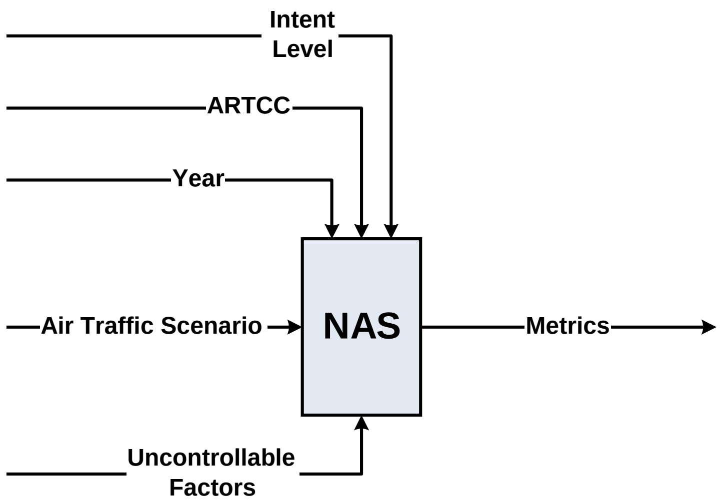


Figure 1: Model of the NAS Process Being Studied

The input to the process in Figure 2 consists of an air traffic scenario and various factors, while the output to be evaluated in this study consists of the trajectory and conflict probe performance. Controllable factors are the year, the airspace, and the intent level. These are described in Section 2.3. As with all processes, there are also uncontrollable factors. The methodology used to simulate the NAS is described in Section 2.5.

The overall approach used in the study is illustrated in Figure 2 and described as follows. The controllable factors are combined as described in Section 2.4 to produce experimental runs with various levels of each factor. Each experimental run uses a scenario file that contains one flight plan for every aircraft in that scenario. This flight plan file is input to the fast-time simulation along with a specified intent level and other simulation-related settings. The output data from the simulation contains track data, clearance amendments, trajectories, and conflict probe alerts and is assumed to represent how the automation system would have behaved with that particular set of flight plans and the specified level of intent entry. Finally, this data is analyzed using specialized tools to evaluate the impact of the various factors.

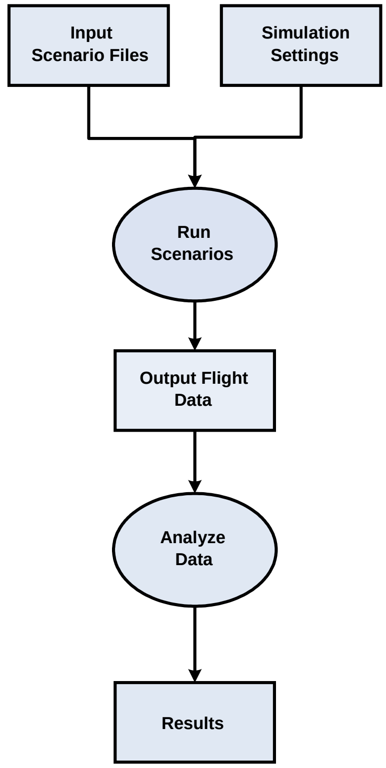


Figure 2: Study Process Flow

Figure 2 depicts the study process. The data, represented by rectangles, consists of input flight scenario files, simulation settings, output data, and analysis results. The processes, represented by ellipses, are the fast-time simulation and analysis of data. The processes are described in Sections 2.5 and 2.7, and the data are described in Sections 2.6 and 3.

2.3 Experimental Factors

Three controllable factors are considered in this study. The level of intent entry to the ground automation is the main factor of interest. Traffic density is a second experimental factor, which is represented by the year for which a traffic scenario is forecast. Finally, differences in air traffic characteristics between Air Route Traffic Control Centers (ARTCC) may affect the responses, so several different centers are selected to demonstrate how the effect from CRA may vary. Thus, the simulation will have three controllable factors:

- percent of clearances fully entered (intent parameter),
- year, and
- ARTCC

which are discussed in the following three sub-sections.

2.3.1 Intent Entry

As mentioned in the previous section, a reduction in the intent that is available to the ground automation is modeled by missing or incomplete amendment clearances. The experimental factor that represents the level of intent entry in the simulation is the percent of 2-part clearances that are fully entered, where the largest percent reflects the highest level of intent entry. Further information about the implementation of this factor is given in Section 2.5. It may be possible to estimate the level of intent entry that CRA would allow, and the current level, by surveying subject matter experts. The model presented in this study allows estimation of the effect at any percent of full 2-part clearance intent entry.

Five levels of this factor will be used in this experiment, making it possible to model intent as a continuous factor. The levels of intent entry to the ground automation system are listed below, along with the 2-letter codes that are used to identify the intent parameter level in each run suffix. Here, “clearances” refers to a full 2-part resolution maneuver.

- Full (FL), 100% of clearances entered
- High (HI), 75% of clearances entered
- Medium (MD), 50% of clearances entered
- Low (LO), 25% of clearances entered
- None (NN), no clearances entered

2.3.2 Traffic Density

Increasing levels of traffic density are simulated by using forecast traffic scenarios. The air traffic scenarios used in this study were flight plan files based on the AJG Forecast Schedules, derived from 2010 traffic levels. This study used two 24-hour scenarios: the AJG 2018 Forecast Schedule and the AJG 2025 Forecast Schedule. The preparation of these scenario files is described in detail in Section 2.6.

2.3.3 ARTCC

This study deals with conflicts identified in five ARTCCs. The five centers are selected based on operational characteristics. The goal is to select center facilities with different characteristics, thus representing a wide range of air traffic operations and automation performance. To aid in this selection, an analysis is performed to categorize all 20 Continental United States (CONUS) ARTCCs based on metrics for conflict probe and trajectory modeling performance and define clusters of centers with similar characteristics. Statistical cluster analysis is employed to quantitatively categorize the centers.

A fast-time simulation is run for the 20 CONUS ARTCCs using historical track data that has been time-shifted to induce realistic conflict events. This method has been used in previous studies [16] as a way to test the performance of trajectory modeling and conflict prediction under circumstances that closely resemble what the automation system would encounter in operation. The resulting data is analyzed to produce conflict probe and trajectory performance metrics and the cluster analysis technique is applied to the data. Cluster analysis seeks to define similar groups of entities based on their characteristics. In this analysis, Ward’s clustering method is performed in JMP® using the following metrics: missed alert rate, false alert rate, average absolute cross track error, average absolute along track error, and average absolute vertical error. These metrics are discussed in more detail in Section 2.7 and [3]. Each of the trajectory error metrics was calculated at 5 minute and 15 minute look ahead time. Five clusters are defined as a result of the analysis, and one ARTCC is selected from each cluster to provide a wide representation of TM and CP performance.

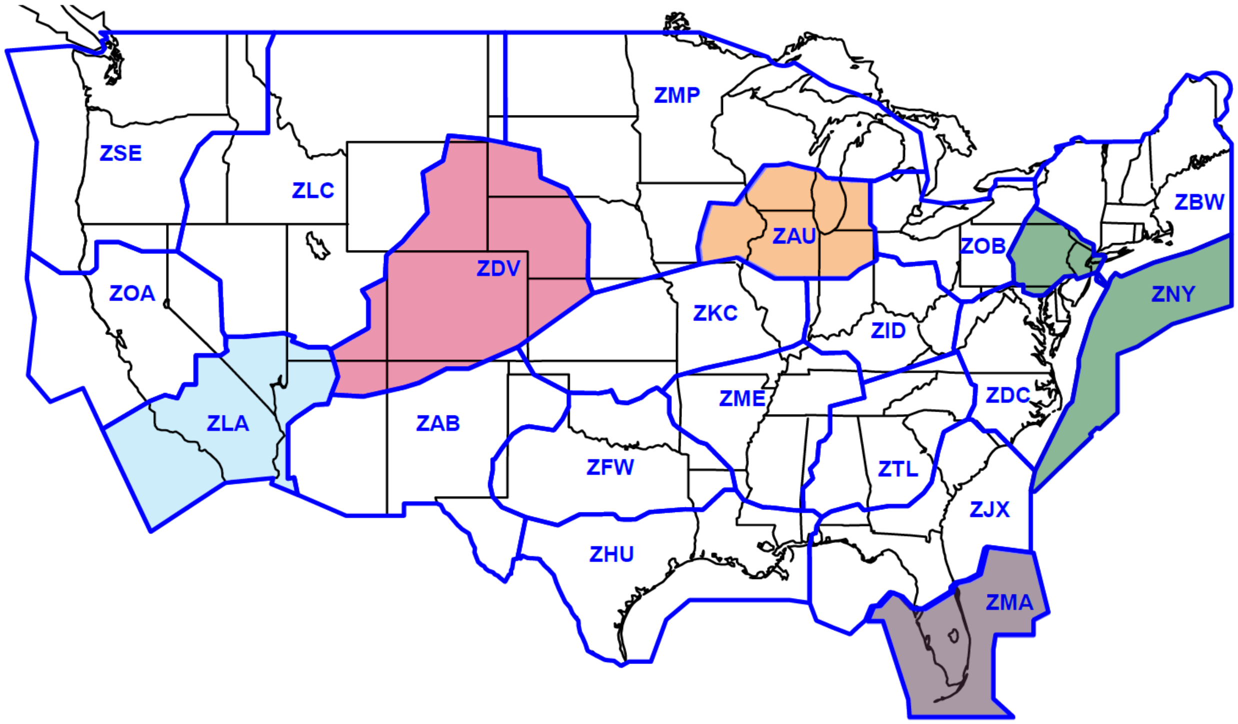


Figure 3: Air Route Traffic Control Centers

The five centers chosen for simulation are: Chicago (ZAU), Denver (ZDV), Miami (ZMA), Los Angeles (ZLA), and New York (ZNY). These centers are highlighted in Figure 3.

2.4 Experimental Design

The levels used for each factor are: two forecast years, five ARTCCs, and five levels of intent entry. As listed in Table 1, forecast year was modeled at 2018 and 2025 traffic levels. The five ARTCCs chosen are: ZAU, ZDV, ZLA, ZMA, and ZNY. The intent parameter has 5 levels, as outlined in Section 2.3.1. The combination of these factors at all levels produces a total of 50 possible experimental runs to study.

Table 1: Summary of Experiment Factors and Levels

Factor	Description of Levels	Number of Levels
Intent Entry	FL, HI, MD, LO,NN	5
Traffic Density (Year)	2018 and 2025	2
ARTCC	ZAU, ZDV, ZLA, ZMA, ZNY	5
	Total Runs =	50

Since it is a fast time simulation study, the marginal cost associated with running individual runs is relatively low. A full factorial design is executed, which includes runs that cover all possible combinations of factor levels. Full factorial designs can be applied to reveal the interaction effects of the factors under study, and are more efficient than simple one factor experiments. The combination of values presented in Table 1 generates a total of 50 simulation runs for the full factorial design. A model will be applied to the responses from the simulation to determine the effect of each factor.

2.5 Fast-Time Simulation

Fast-time simulation is used to generate track data for input flight plans, simulate CRA amendments, and create scenarios reflecting different levels of intent entry. This process is described in detail in Section 3.1 of [10] and summarized here. The fast-time simulation framework is detailed in [10] and uses MITRE's Java En Route Development Initiative (JEDI) because it has trajectory modeling and conflict detection with functional performance similar to ERAM [12].

The process starts with an input file containing one flight plan for each aircraft, from which track data is generated using a track simulator. Any predicted loss of separation between flights detected in this track data is resolved using a MITRE-CAASD problem resolution prototype named Problem Analysis Resolution and Ranking (PARR), a prototype of CRA. The resolution of notified conflicts (alerts) by PARR is invoked on a one minute cycle. For each notified conflict the highest ranked resolution is chosen and sent to the track simulator, which then simulates track data that follows the resolution.

In the full intent scenarios, the resolution amendments are also sent to the Flight Manager (JEDI) for modeling. However, in a reduced intent scenario, some of this resolution information is withheld from the Flight Manager, depending on the specified intent level. This difference in information is what distinguishes the intent parameter, and it is implemented based on the factor level. For instance, at the NN or "no intent" level, the track simulator receives full two-part altitude and lateral amendments, while Flight Manager receives only interim altitudes for vertical resolution amendments, and no information at all for two-part lateral resolution amendments. At the MD or "medium intent" level, these types of resolutions have a 50% chance of being sent to the Flight Manager. Cases where Flight Manager receives missing or incomplete intent information are referred to as reduced intent amendments.

Alerts for which a resolution is sent to the track simulator are not resolved in future resolution cycles because any implemented resolution is assumed to be following a green, or conflict-free, flight plan. The Current Plan look-ahead determines how far along the current flight path the conflict probe is applied and is set to 10 minutes for this experiment, with resulting alert notification time between 4 and 10 minutes based on conflict likelihood. Trial Plan conflict detection establishes the required time for which a resolution path must be conflict free and is set at a 12 minute look ahead, which effectively ensures that any proposed resolution will be conflict free for at least 12 minutes.

2.6 Data Preparation

ANG-C41 created the input flight plan scenarios for this study by using the FAA's Joint Planning Group (AJG) Forecast Schedules. These estimate future air traffic demand and are 24-hour scenarios representing air traffic over the entire NAS, including international flights. The forecast schedules were used as a basis for air traffic scenarios representing potential flight traffic in the years 2018 and 2025. The scenario input files are generated using established tools, including the *ATOPScheduleConverter*, from the Conflict Probe Assessment Team (CPAT) within ANG-C41. To limit each scenario to a specific ARTCC, air traffic was filtered to include only those flights traveling through some part of the ARTCC. In addition, recorded flight data was analyzed to calculate a representative distribution of aircraft equipage codes by aircraft type which was then assigned to the flight plans.

Table 2 provides a summary of the traffic counts in each of the runs for the five centers. The number of flights in each scenario output from the fast-time simulation is slightly less than the input number due to flights not reaching the center airspace before the end of the scenario and other simulation issues. These final counts are presented on the right hand side of Table 2.

Table 2: Number of Flights

	Input Flight Plans		Simulation Output	
	2018	**2025**	**2018**	**2025**
ZAU	4931	5695	4462	5126
ZDV	3714	4326	3343	3879
ZLA	4183	4868	3795	4393
ZMA	4675	5587	4052	4790
ZNY	6532	7494	5204	5864
Total	24035	27970	20856	24052

There are 10 unique input files, which account for five different ARTCCs and two levels of traffic density. The remaining factor, intent level, was implemented as a simulation input parameter as discussed in Section 2.5.

2.7 Analysis Tools

Metrics to compare the proposed environment to the current environment are needed in quantifying the benefit of the proposed changes. Existing tools from CPAT will be utilized in this analysis as detailed in the following subsections.

2.7.1 Trajectory Modeling Analysis

The output simulation data includes predicted trajectories generated by JEDI's trajectory modeling and used by the conflict probe in detection. When a reduced intent amendment is issued, the trajectory modeling system is lacking the necessary information to update the cleared flight plan and build an accurate long-term trajectory. The result of this is that the flight's actual path will deviate from the known route and a new trajectory must be built. In a reduced intent scenario, the trajectory reconformance algorithm uses default parameters to estimate the turn point or altitude transition point of an aircraft, in the case of a two-leg vector or step altitude maneuver, respectively. It is anticipated that in the reduced intent scenarios, new trajectories will be generated more frequently which increases trajectory instability and degrades the conflict probe performance.

To quantify this change, the number of unique trajectories built by the automation for each unique aircraft identification (ACID) is recorded. Another count is made which identifies a specific subset of these trajectories. Every time an amendment is entered, a new trajectory is generated. To focus on trajectories that were built for other reasons, amendments are matched to trajectories by ACID and time (within one second) to identify cases other than when a trajectory is built following an amendment.

It is anticipated that reduced intent amendments may negatively affect the accuracy of the predicted trajectories, which also contributes to degraded conflict probe performance. Trajectory error metrics have been applied in previous studies to provide a method to measure the accuracy of trajectories in multiple dimensions with respect to actual flight position. This provides a means of quantifying the effects of improved intent. Sampling methods and definitions of these metrics are presented in [3] and summarized here briefly. The Interval Based Sampling Technique (IBST) is the trajectory accuracy sampling method developed by ANG-C41. It has been previously documented in [15] and has been used in a number of FAA studies and test programs. IBST is a two-step process that pairs track and trajectory points to measure the prediction errors for an entire flight.

The four basic metrics defined in [15] are horizontal error, vertical error, along track error, and cross track error. Figure 4 provides a notional illustration of these errors. The horizontal error is the time coincident difference in NM between the predicted position on the trajectory and the actual position calculated from surveillance radar reports. Cross track error (NM) is the perpendicular distance between the actual position of an aircraft and its projection onto the trajectory. Along track error (NM) is the longitudinal distance along the trajectory between the same projection and the time coincident predicted position of the aircraft. The vertical error (not illustrated in the figure) is the altitude difference in feet between the predicted trajectory position and the time coincident actual position. For further details on these definitions and how they are calculated see [15].

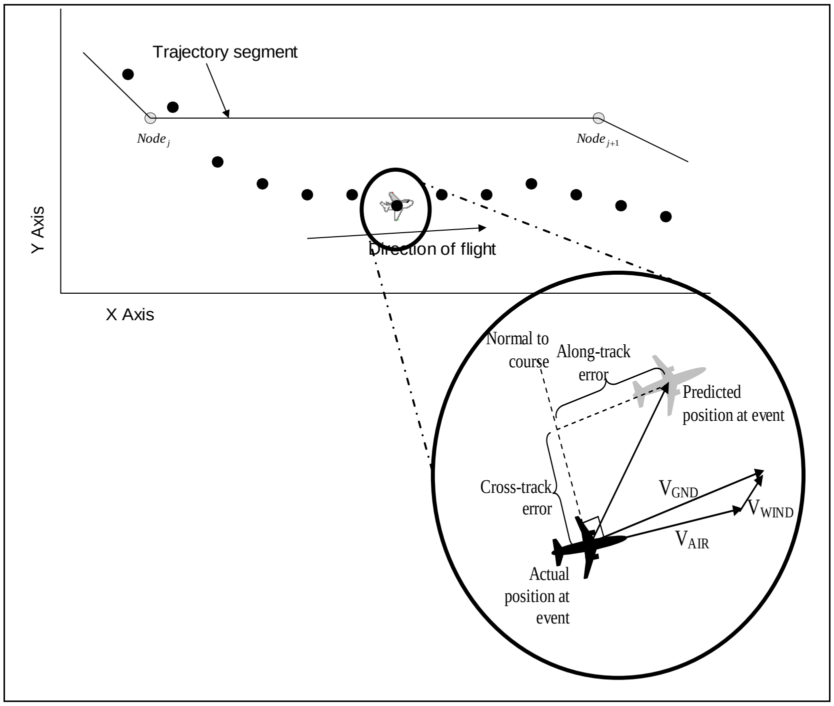


Figure 4: Diagram of Trajectory Errors

Following these definitions, horizontal error is unsigned while the other three are signed. For most analyses involving these metrics, it is desirable to consider absolute values because the distance from zero is of interest. Therefore the absolute value is taken before calculating average values. Finally, the average metrics comprise only relevant data points by considering error values for trajectory points where a clearance or route amendment has not been received within a specified time period (as that may have altered the trajectory) and the flight remains within control of the center.

CPAT tools are used to parse trajectory information from the JEDI output data into a database format. The information is then processed to count the total unique trajectories and unique trajectories that are not matched to a clearance amendment. Finally, the CPAT tool *TrajectorySampler* performs the trajectory error sampling.

2.7.2 Conflict Probe Alert Analysis

The available track data in the scenarios has been processed through conflict detection, with resolution maneuvers implemented. Using this data, there is no guaranteed way to determine whether the potential loss of separation for which an alert is generated would actually have materialized, or how close it would have been without action from ATC. Therefore, this study will not analyze the performance of generated alerts in terms of traditional accuracy (e.g., false alerts and missed alerts)[2]. Instead the focus of this analysis is on the notification sets and alert-related metrics such as alert counts, duration, and predicted warning time.

CPAT tools are used to analyze the alert information output from the simulation runs to identify distinct alert notifications using rules specified in [3]. The count of distinct alert notifications is compared across the scenarios and used as a response variable in the statistical model.

The duration of each alert notification is calculated as the difference between the latest alert deletion time and the earliest alert add time in a given set. It is expected that in cases of reduced intent amendments as mentioned in Section 2.5, alerts will not be removed upon resolution. Since the resolution algorithm attempts to resolve conflicts every minute, alert durations greater than 1 minute are indicators of problematic alerts.

The predicted warning time provided by an alert is calculated as the notification start time subtracted from the predicted conflict start time. The distribution of warning times is analyzed across the various scenarios. A shift in the warning time distribution may indicate a degradation in conflict probe performance. Therefore the 25th percentile, or first quartile (Q1), of the alerts' predicted warning times is calculated as a metric of interest in tracking the CP performance.

2.7.3 JMP

JMP® is an interactive data visualization and statistical analysis tool available through the SAS Institute.[3] ANG-C41 has used JMP® successfully in many other studies [17][18]. It was used extensively for the data analysis in this study because of its ability to interface directly with ANG-C41's Oracle® databases to provide data tables, graphs, charts, and reports and because of its ability to provide statistical analyses and modeling capabilities including support of the study's Design of Experiment (DOE).

3. Results

This section presents the results of the experiment in four sub-sections. Section 3.1 deals with the performance of the trajectory modeling in terms of the accuracy of the predicted trajectory positions and the number of trajectory rebuilds that are generated during the simulation. General descriptive statistics are provided in addition to testing for statistical differences between treatment scenarios. Section 3.2 investigates the performance of the conflict probe and specifically, the alerts generated by the simulated automation system that would have been shown to controllers interacting with the system tool. Metrics from each of these first two sections are selected as response variables in a statistical model in Section 3.3, which discusses how the model is fit to the experiment data to determine the effects of the different factors and their interactions. Finally, specific examples of improvement with increased intent are presented in Section 3.4. The examples are taken from the simulated flight data of two scenarios.

2 Traditional conflict prediction metrics or a version of such will be left for future study.
3 The SAS Institute Inc., SAS Campus Drive, Cary, NC 27513.

3.1 Trajectory Modeling Performance

The following two subsections provide a descriptive and inferential statistical analysis of the trajectory modeling in the simulated data. The accuracy and stability of predicted trajectories are key to the overall performance of the ERAM system and conflict probe.

3.1.1 Counts of Trajectories

As stated in Section 2.7.1, new trajectories are built when aircraft track data do not adhere to the known route. The trajectory reconformance algorithm is forced to guess a turn point or altitude transition to rejoin the known route and this is likely to result in trajectories with poor prediction accuracy and, in turn, further trajectory rebuilds. It is expected that reduced intent scenarios will result in more frequent deviations from the known route and more frequent generation of new trajectories. The number of trajectories generated per ACID is analyzed to quantify the effect of improved intent and the results are presented in this section.

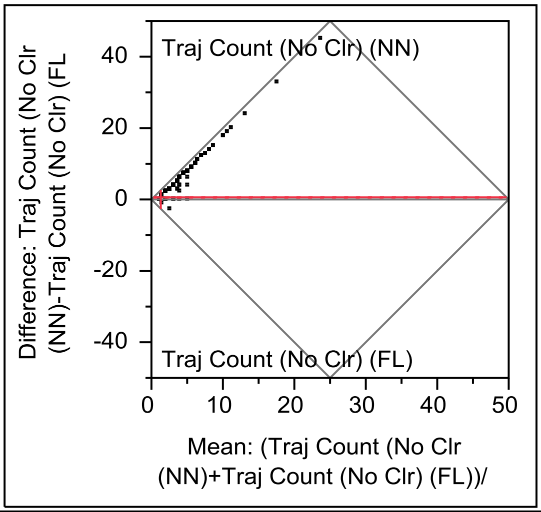
The number of unique trajectories, distinguished by the trajectory build time, for each flight in a scenario is recorded. These counts are averaged over all of the flights in a scenario, and the average (per flight) values are presented in Table 3. The scenario data are grouped by the factors ARTCC, Year, and Intent Level.

Table 3: Average Total Trajectory Count by Scenario

ARTCC	Year	Intent	Average Total Trajectory Count
ZAU	2018	FL	2.9
		HI	3.1
		MD	3.4
		LO	3.6
		NN	3.9
	2025	FL	3.0
		HI	3.2
		MD	3.4
		LO	3.7
		NN	4.0
ZDV	2018	FL	2.5
		HI	2.7
		MD	2.8
		LO	3.0
		NN	3.2
	2025	FL	2.6
		HI	2.8
		MD	3.0
		LO	3.1
		NN	3.3

ARTCC	Year	Intent	Average Total Trajectory Count
ZLA	2018	FL	2.8
		HI	3.0
		MD	3.4
		LO	3.6
		NN	3.9
	2025	FL	2.9
		HI	3.2
		MD	3.5
		LO	3.9
		NN	4.2
ZMA	2018	FL	2.9
		HI	3.1
		MD	3.3
		LO	3.6
		NN	3.8
	2025	FL	3.0
		HI	3.2
		MD	3.4
		LO	3.7
		NN	4.0
ZNY	2018	FL	2.9
		HI	3.1
		MD	3.3
		LO	3.6
		NN	3.8
	2025	FL	2.9
		HI	3.2
		MD	3.4
		LO	3.7
		NN	3.9

There are clear trends in Table 3 of count values decreasing with improved intent entry. To verify that this effect is significant, a statistical test is applied to the data. Each of the four reduced intent scenarios is considered as a treatment run and compared against the full intent scenario (FL, or 100% of clearances entered into automation) using a paired *t*-test. The same flights are present in all five scenarios for a specified Year and ARTCC, so the trajectory count for each flight in a treatment run is compared to the trajectory count for the same flight in the full intent run. The paired *t*-test examines the distribution of differences in counts between the two scenarios, and tests if the mean of the differences is statistically different from zero. The results of an example *t*-test are presented in Figure 5.



Traj Count (No Clr) (NN)	1.59868	t-Ratio	17.34
Traj Count (No Clr) (FL)	1.01709	DF	3627
Mean Difference	0.58159	Prob > |t|	<.0001*
Std Error	0.03354	Prob > t	<.0001*
Upper 95%	0.64734	Prob < t	1.0000
Lower 95%	0.51583		
N	3628		
Correlation	0.08046		

Figure 5: Paired *t*-test Results for Trajectory Count in ZDV 2018 Scenarios

From Figure 5 the difference in trajectory counts can be observed. The *p*-value is identified as "Prob > *t*" because it is the random probability of generating a *t*-statistic greater than 17.34, and in this example it is very small which supports the determination that the difference is statistically significant. One paired *t*-test is done for each of the four reduced intent scenarios in a given ARTCC and Year, for a total of 40 tests. The same conclusion is reached, that the trajectory counts are lower overall in the full intent scenario than in the reduced intent scenarios. This difference is statistically significant in all comparisons, with all *p*-values less than 10^{-4}. Table 13 in Appendix A contains the difference in means and Student's paired *t*-statistic for each comparison.

The second type of trajectory count is a subset of the total trajectory count. The reason for defining this metric is that more clearance amendments are entered, and therefore more trajectories are generated, as the level of intent decreases between scenarios. The metric is designed to account for this increase and focus on the generation of additional trajectories. As explained in Section 2.7.1, entered amendments are matched to generated trajectories with the same ACID and occurring within one second, and the trajectories that are not matched to a clearance are counted. This represents how many "extra" trajectories are generated in a scenario. The counts are averaged over all of the flights in a scenario, and the averages are presented in Table 4, grouped by factors similar to the previous table.

Table 4: Average Count of Trajectories Not Matched to a Clearance

ARTCC	Year	Intent	Average Trajectory Count
ZAU	2018	FL	1.1
		HI	1.3
		MD	1.5
		LO	1.7
		NN	1.9
	2025	FL	1.1
		HI	1.3
		MD	1.5
		LO	1.7
		NN	2.0
ZDV	2018	FL	1.0
		HI	1.2
		MD	1.3
		LO	1.5
		NN	1.6
	2025	FL	1.0
		HI	1.2
		MD	1.4
		LO	1.5
		NN	1.7
ZLA	2018	FL	1.0
		HI	1.2
		MD	1.5
		LO	1.7
		NN	2.0
	2025	FL	1.0
		HI	1.3
		MD	1.5
		LO	1.9
		NN	2.2
ZMA	2018	FL	1.1
		HI	1.2
		MD	1.4
		LO	1.6
		NN	1.8
	2025	FL	1.1
		HI	1.3
		MD	1.4
		LO	1.6
		NN	1.9

ARTCC	Year	Intent	Average Trajectory Count
ZNY	2018	FL	1.1
		HI	1.3
		MD	1.4
		LO	1.7
		NN	1.8
	2025	FL	1.1
		HI	1.3
		MD	1.5
		LO	1.7
		NN	1.9

Again, there are clear trends in Table 4 of count values decreasing with improved intent. Similar to the analysis for total trajectory count, a paired *t*-test is applied to the data to verify that the effect is significant. Comparing each reduced intent scenario to the corresponding full intent scenario, the difference for each flight is calculated. A paired *t*-test determines whether the mean of the differences is statistically different from zero. Similar to the full trajectory count analysis, 40 tests are done and the results presented in Table 13 in Appendix A. The same determination of statistical significance is reached in all cases: the counts of extra trajectories in a reduced scenario are lower overall than in the full intent scenario. In these tests, the *p*-values are all less than 10^{-4} and the Student's paired *t*-statistic values are compared to the results for total trajectory counts in Table 13. The results show that, even after accounting for an increase in trajectory generation from increased issuance of clearances, the effect of improved intent on trajectory generation is significant.

3.1.2 Trajectory Accuracy

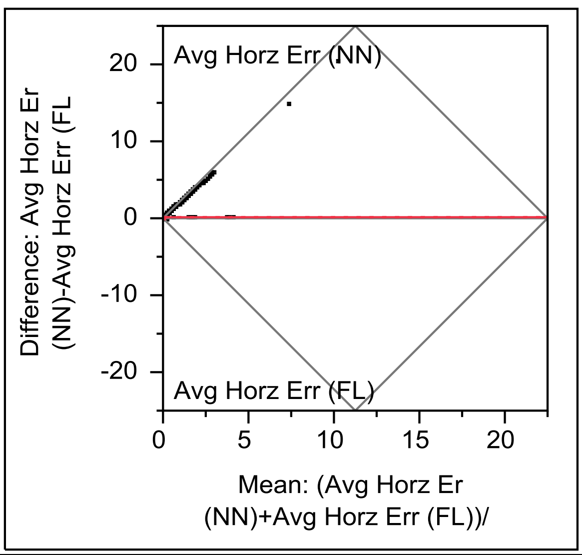
To quantify the effect of improved intent entry on the accuracy of predicted trajectories, the IBST is applied to the trajectories and simulated track data as detailed in Section 2.7.1. The resulting trajectory error metrics are compiled and presented here. First, the average of absolute cross track error values (denoted as AACTE) is calculated for each flight in a given scenario, taking into account all desired sampled points for that flight. The average of this value is then calculated over all flights in the scenario and presented in Table 5 to illustrate the general trend in accuracy between scenarios. The same process is used to compile average absolute along track error (AAATE) in NM, average absolute vertical error (AAVE) in feet, and average horizontal error (AHE), which is unsigned and expressed in NM. The average values by scenario for these four trajectory error metrics are presented in Table 5. The scenarios are grouped by ARTCC, Year, and Intent Level.

Table 5: Average Error Metrics by Scenario

ARTCC	Year	Intent	Avg AACTE (NM)	Avg AAATE (NM)	Avg AAVE (ft)	Avg AHE (NM)
ZAU	2018	FL	0.030	0.143	87	0.155
		HI	0.062	0.169	97	0.205
		MD	0.106	0.203	111	0.272
		LO	0.157	0.237	127	0.343
		NN	0.208	0.244	143	0.388
	2025	FL	0.028	0.140	87	0.151
		HI	0.061	0.176	100	0.211
		MD	0.112	0.203	116	0.276
		LO	0.160	0.249	132	0.354
		NN	0.227	0.260	147	0.415
ZDV	2018	FL	0.021	0.044	13	0.049
		HI	0.046	0.063	17	0.089
		MD	0.075	0.074	19	0.124
		LO	0.112	0.093	23	0.171
		NN	0.132	0.096	28	0.190
	2025	FL	0.021	0.042	15	0.050
		HI	0.058	0.071	19	0.106
		MD	0.076	0.078	21	0.128
		LO	0.107	0.088	28	0.164
		NN	0.136	0.103	32	0.199
ZLA	2018	FL	0.026	0.088	52	0.098
		HI	0.053	0.123	61	0.145
		MD	0.105	0.161	72	0.227
		LO	0.157	0.194	79	0.283
		NN	0.227	0.235	97	0.367
	2025	FL	0.028	0.093	55	0.103
		HI	0.079	0.141	69	0.192
		MD	0.160	0.194	77	0.301
		LO	0.216	0.230	95	0.378
		NN	0.312	0.296	116	0.500
ZMA	2018	FL	0.022	0.128	74	0.124
		HI	0.039	0.155	86	0.159
		MD	0.071	0.178	103	0.210
		LO	0.097	0.200	116	0.246
		NN	0.126	0.205	132	0.273
	2025	FL	0.023	0.139	74	0.133
		HI	0.055	0.162	87	0.180
		MD	0.073	0.183	104	0.215
		LO	0.113	0.201	121	0.263
		NN	0.166	0.225	142	0.325

ARTCC	Year	Intent	Avg AACTE (NM)	Avg AAATE (NM)	Avg AAVE (ft)	Avg AHE (NM)
ZNY	2018	FL	0.036	0.234	88	0.220
		HI	0.072	0.279	102	0.286
		MD	0.090	0.308	108	0.324
		LO	0.134	0.327	127	0.379
		NN	0.169	0.348	136	0.420
	2025	FL	0.039	0.234	94	0.226
		HI	0.061	0.282	109	0.283
		MD	0.097	0.295	114	0.323
		LO	0.139	0.349	132	0.400
		NN	0.176	0.368	146	0.440

There are clear trends in the Table 5 data of trajectory accuracy increasing (error values decreasing) with improved intent. To verify that this effect is statistically significant, a paired *t*-test is applied to the data. Each of the four reduced intent scenarios is compared against the corresponding full intent scenario. The same flights are present in all five scenarios for a specified Year and ARTCC, and the average trajectory error for each flight in a reduced intent scenario is compared to the average error for the same flight in the full intent scenario. The results of an example *t*-test are presented in Figure 6.



Avg Horz Err (NN)	0.18985		t-Ratio	11.53
Avg Horz Err (FL)	0.04948		DF	3337
Mean Difference	0.14037		Prob > |t|	<.0001*
Std Error	0.01218		Prob > t	<.0001*
Upper 95%	0.16425		Prob < t	1.0000
Lower 95%	0.11649			
N	3338			
Correlation	0.17383			

Figure 6: Paired *t*-test Results for Trajectory Error in ZDV 2018 Scenarios

From Figure 6 the difference in trajectory accuracy can be observed. The Student's paired *t*-statistic is calculated as 11.53, with an associated *p*-value less than 0.0001. This probability is very small and supports the determination that the difference is statistically significant. Four paired *t*-tests (one each for

AACTE, AAATE, AAVE, and AHE) are done for each of the four reduced intent scenarios in a given ARTCC and Year, for a total of 160 tests. The same conclusion is reached, that trajectory errors are lower overall in the full intent scenario than in the reduced intent scenarios. This difference is statistically significant in all comparisons, with all *p*-values less than 10^{-3}. Table 14 in Appendix B contains the difference in means and Student's paired *t*-statistic for each comparison.

A different analysis approach is to consider the trajectory errors at a specific amount of time into the future, or look ahead time. This allows for evaluation of the trajectory predictor performance trend with look ahead time, and comparison of how this trend is affected by improved intent. The average absolute cross track error for a given look ahead time and all sampled points is calculated for 0, 300, 600, 900, and 1200 second look ahead times (every 5 minutes) and presented in Figure 7 for the set of ZAU (2018 and 2025) scenarios. The legend lists the scenarios in the same order in which they appear in the graphs.

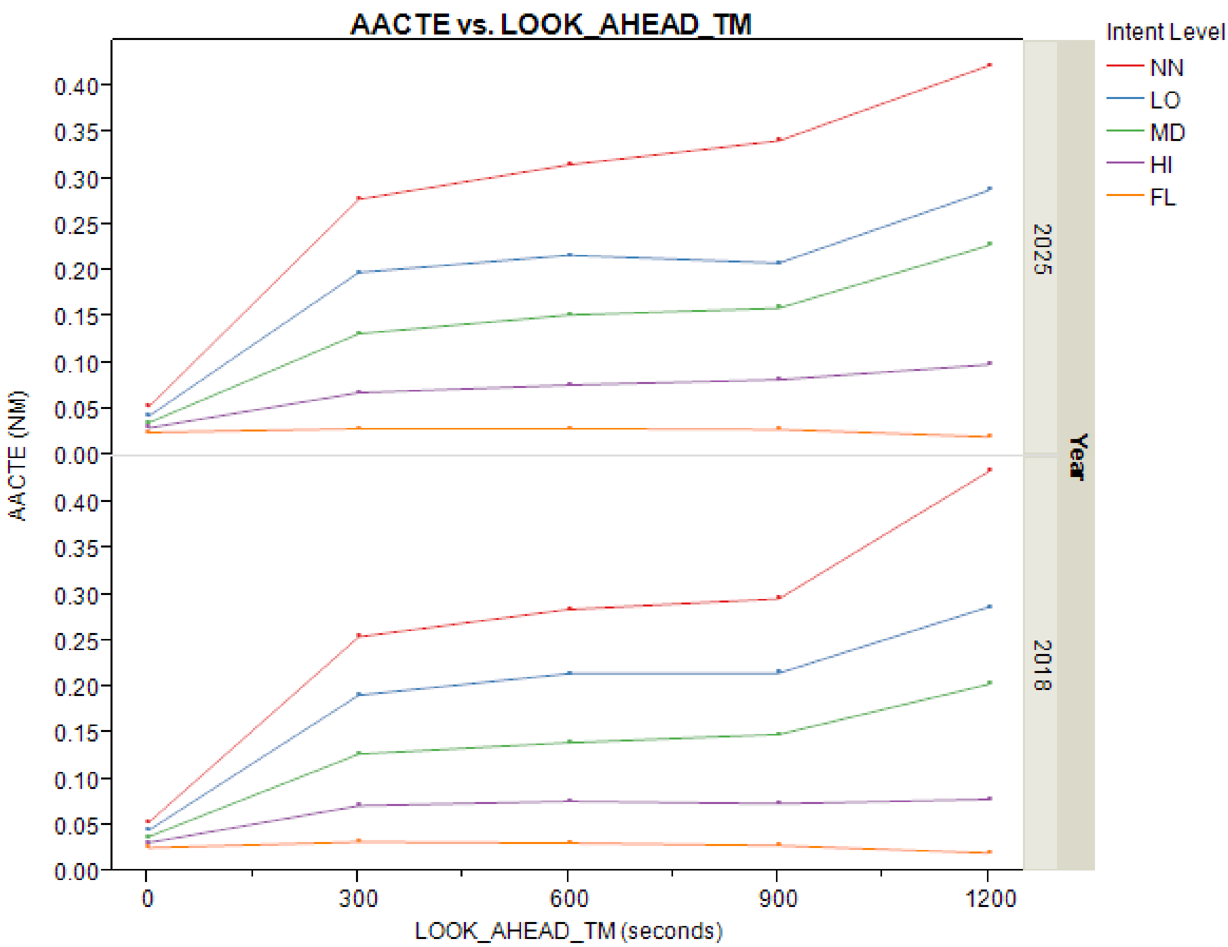


Figure 7: Trajectory Error vs. Look Ahead Time

From Figure 7 it is observed that an increase in the level of intent entry corresponds to a decrease in average absolute cross track error at every look ahead time for the ten scenarios shown. In addition, the benefit from increased intent entry is more pronounced at longer look ahead times. Similar graphs for vertical and along track errors are located in Appendix C. It is noted that the relative differences are smaller for vertical error, and there is a slight inconsistency in the pattern for along track error.

3.2 Conflict Probe Alert Performance

Conflict alerts generated by the automation are collected for each simulated scenario. Alert addition, modification, and deletion events are grouped into notification sets using CPAT tools with specially designed logic. These notification sets are analyzed for overall count, alert duration, and predicted warning time to demonstrate benefits from improved intent entry. The count of distinct alert notifications is presented in Figure 8.

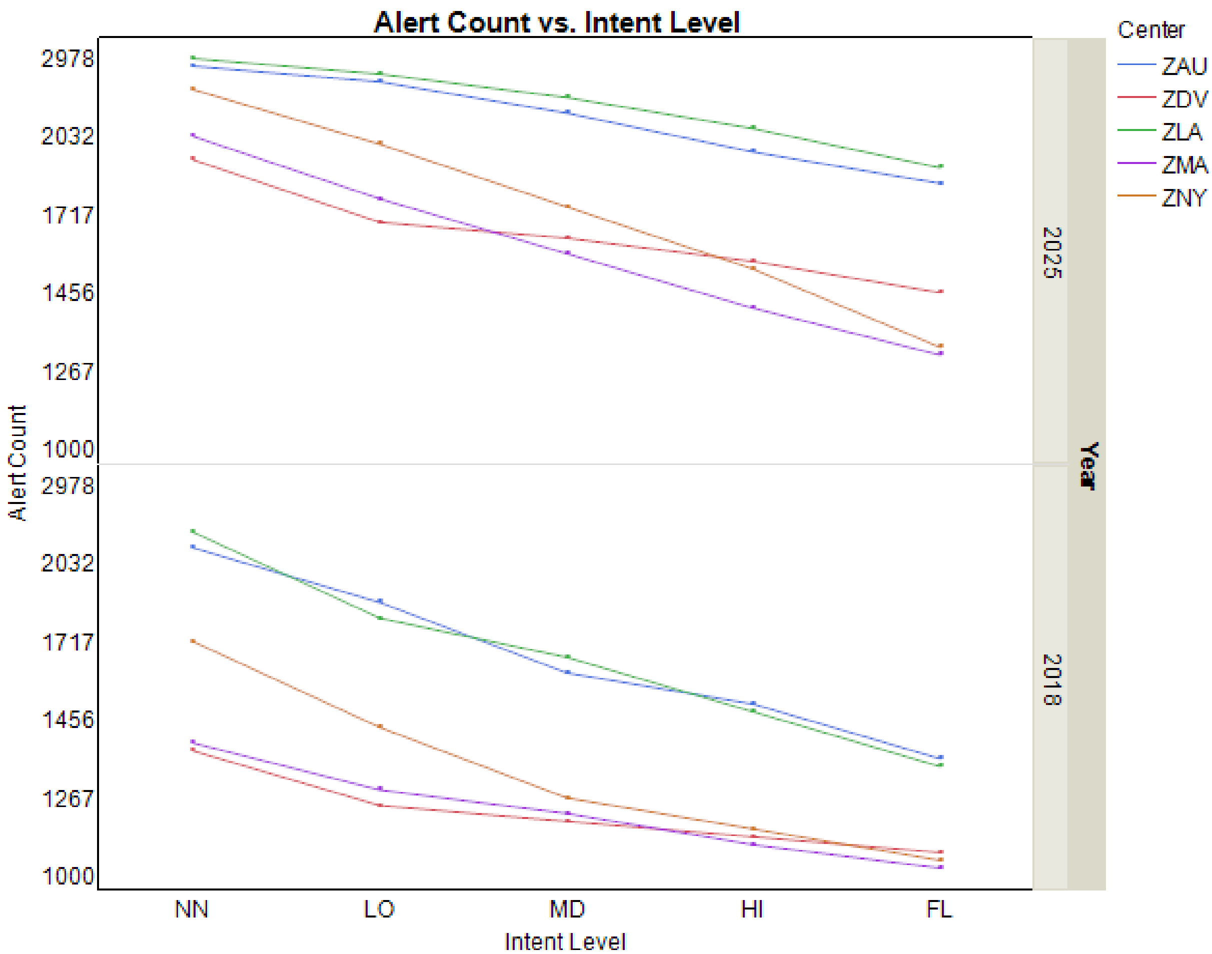


Figure 8: Alert Count vs. Intent Level

From Figure 8, the trend in each center is a consistent decrease with increased intent level, regardless of traffic year. These trends differ across the various centers. In particular, ZDV exhibits slightly different behavior, although the counts do follow the general trend of decreasing with increased intent level. These types of differences may be investigated in future studies.

Due to open clearances in reduced intent scenarios, it is expected that a significant number of alerts will not be removed upon issuing an amendment, whereas with full intent, the majority are successfully resolved and the alerts deleted. Alerts with duration greater than 60 seconds are depicted in Figure 9, which provides the distribution of alert duration in one minute intervals. Since the resolution algorithm attempts to resolve alerts every minute, these can be interpreted as alerts that are not deleted at the time an amendment is entered. The percentage of problematic events over all events allows for a relative measure of performance between the scenarios. It is expected that improving the ground automation will diminish this percentage and it is hypothesized here that providing better intent information will improve the related automation functions. The percent of alerts with long duration metric was computed for all scenarios and aggregate percentages are, from most intent to least intent provided: 15.6%, 21.5%, 26.3%, 28.9%, and 34.0%. These data are further detailed by partitioning the event durations into increments of one minute. Figure 9 illustrates the metric over the five intent levels for ZAU with 2018 traffic and provides evidence that as intent is increased, the percentage of problematic events decreases. The other scenarios show a similar relative pattern and are included in Appendix D.

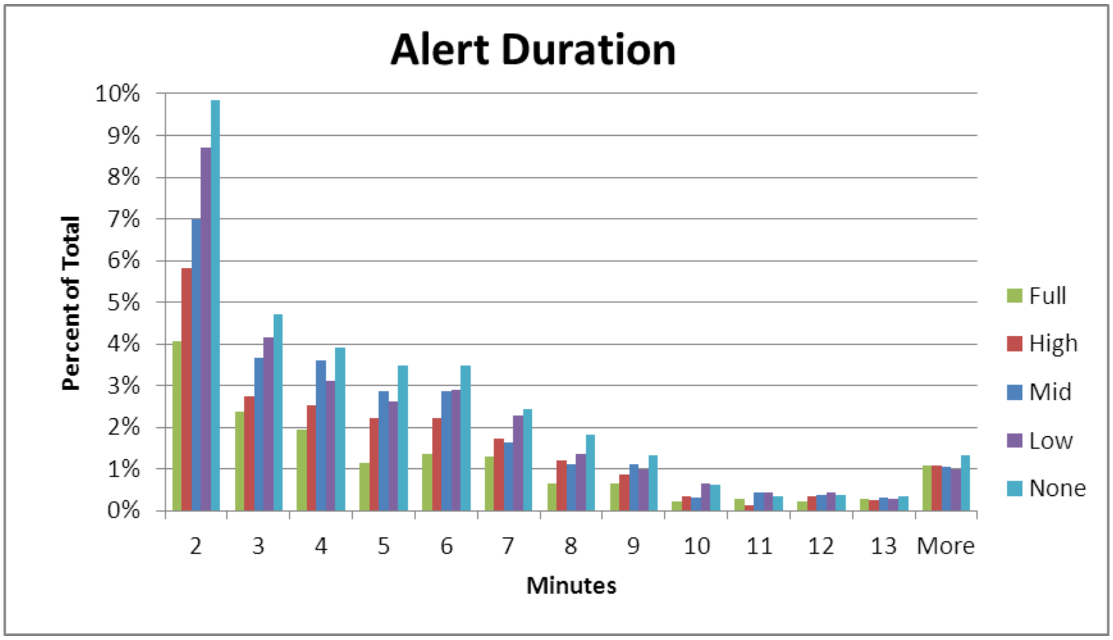


Figure 9: Percent of Alerts with Duration Exceeding One Minute

Another result of inaccurate trajectories from reduced intent amendments is an increase in the frequency of late notification of alerts. One factor that contributes to this increase is a short problem detection look ahead during the first off-leg of a vector maneuver or the level segment of a step altitude maneuver. For instance, if a modeled segment length has shorter duration than the controller's true intention, potential conflicts may only be alerted after a reconformance trajectory extending the off-leg or level segment is built, and accordingly these alerts may have a relatively small warning time. The first quartile of the predicted warning time is a valuable metric to describe how the lower tail of the distribution is affected by a change.

To demonstrate how the predicted warning time distribution is affected, Table 6 presents data from ZAU, grouped by intent level and year. Count is the number of alerts generated, and Percent of Alerts with Duration > 1 min. represents the aggregated percentages from the previous histograms. Q1 of Predicted Warning Time is the 25^{th} percentile of the warning times predicted by the alerts (predicted conflict start time – notification start time) in seconds.

Table 6: Alert Statistics for ZAU Scenarios

ARTCC	Year	Intent	Count	Q1 of Predicted Warning Time (seconds)	Percent with Duration > 1 min.
ZAU	2018	FL	1381	291	15.6
		HI	1494	282	21.5
		MD	1635	270	26.3
		LO	1829	240	28.9
		NN	2103	199	34
	2025	FL	1812	292	14.3
		HI	1939	283	18.9
		MD	2116	273	24.1
		LO	2351	244	28.9
		NN	2713	208	33

In general, the number of alerts created increases as the intent level decreases, as is expected, though there is one anomalous value for ZDV 2018 with low intent level. Q1 of the predicted warning time represents the minimum predicted warning time for three-quarters of the data set, so decreasing this value represents a degradation of the minimum expected warning time predicted by the majority of alerts. This metric provides an alternate way of showing change in performance and supports the histograms, represented in aggregate form in the tables as Percent Alerts with Duration > 1 min. They support each other since one shows degradation in performance via predicted warning time decreasing and the other shows this via an increasing percentage of problematic alerts. Similar tables for the other four centers are provided in Appendix E.

3.3 Statistical Model of Experiment Results

The results of implementing the inferential statistical approach are presented in this section. A detailed multivariate regression model is used to fit the results of the designed experiment with the goal of determining which factors have a significant effect on the response variables and the size of these effects. Metrics from trajectory modeling and conflict alert performance are selected as response variables for the model. Section 3.3.1 implements a statistical model and describes how the experiment data is fitted to the model, while Section 3.3.2 discusses the findings from the model.

3.3.1 Model Implementation

Equation 1 illustrates the mathematical model for this experiment. It represents the full factorial design where all levels and factors are crossed, allowing all the interactions to be examined. This amounts to three main effects (single variables), three two-way interaction terms (double variables), and a quadratic term on the continuous variable, intent level. The constant or overall mean effect is represented as the "μ"term.

Response:

$$R_{ijk} = \mu + Y_i + A_j + I_k + Y_i \times A_j + Y_i \times I_k + A_j \times I_k + I_k \times I_k + \varepsilon_{n(ijk)}$$ **Equation 1**

Where:

Y_i = forecast years, i = 1, 2
A_j = ARTCC, j = 1, 2, 3, 4, 5
I_k = intent level, k = 1, 2, 3, 4, 5
$\varepsilon_{n(ijk)}$ = random error, n = 1, 2, … for all i, j, k

The model assumes the random error $\varepsilon_{n(ijk)}$ is approximately independently normally distributed with a zero mean and that the various factors are linearly additive as illustrated in Equation 1.

Five response variables are evaluated and the same model in Equation 1 addresses all five separately. Thus, the term, "R_{ijk}," can refer to any one of the response variables. These values are calculated for each of the various runs (and associated factor levels) defined in Table 1. The term "R_{ijk}" then is an estimate of the expected value for each of these five output functions. The response variables studied with this model are: average absolute horizontal trajectory error, average absolute vertical trajectory error, the count of trajectories with no associated clearance, the first quartile of predicted warning time, and the count of alerts with duration greater than one minute.

An experimental design is presented in Section 2.4. As coded in Equation 1 and described in Table 1, this design is referred to as a full factorial design in the literature [1][9][14][17]. A full factorial design includes all possible combinations of factor levels in the experiment. It is expensive in terms of runs required but offers several advantages, especially early in the study of a process. In this study, the quantity of runs is relatively inexpensive because a fast-time simulation model is employed. Factorial designs can be used to reveal the interaction effects of the factors under study and they are significantly more efficient than many one-factor experiments. The combinations of factor levels provide replications for evaluation of the individual factors, when some factors or factor combinations are removed from the experiment. The full factorial experiment described in Section 2.4 is implemented and the results from the 50 experimental runs are collected and the model is fit to the calculated response data.

3.3.2 Model Findings

The fitted model is summarized graphically in Figure 10, where five leverage plots illustrate the actual and modeled values for each of the five responses. If the model could perfectly capture all the observed variation in the system, the actual measured response mean plotted on the y-axis in the figures and the coincident modeled version on the x-axis would fall on a diagonal line perfectly. The term "Rsq" in the plots is the coefficient of determination of the model.[4] This term provides a quantification of how well the model captures the observed variation in the system under study. For the five response variables under study in this experiment, the R^2 ranged from 0.97 to 1.00. In practical terms, this means that the model defined in Equation 1 captured from 97 to 100 percent of the variation in the actual system under study. It is clear for all five responses that the model captures the trend and a high percentage of the variation.

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4 From Ref. [8], the R^2 is the coefficient of determination and is equal to the ratio of the sum of squares of the model divided by the sum of squares of the total variation. The total variation equals the modeled variation plus the error in the model (estimated by calculating the difference between model and observed values).

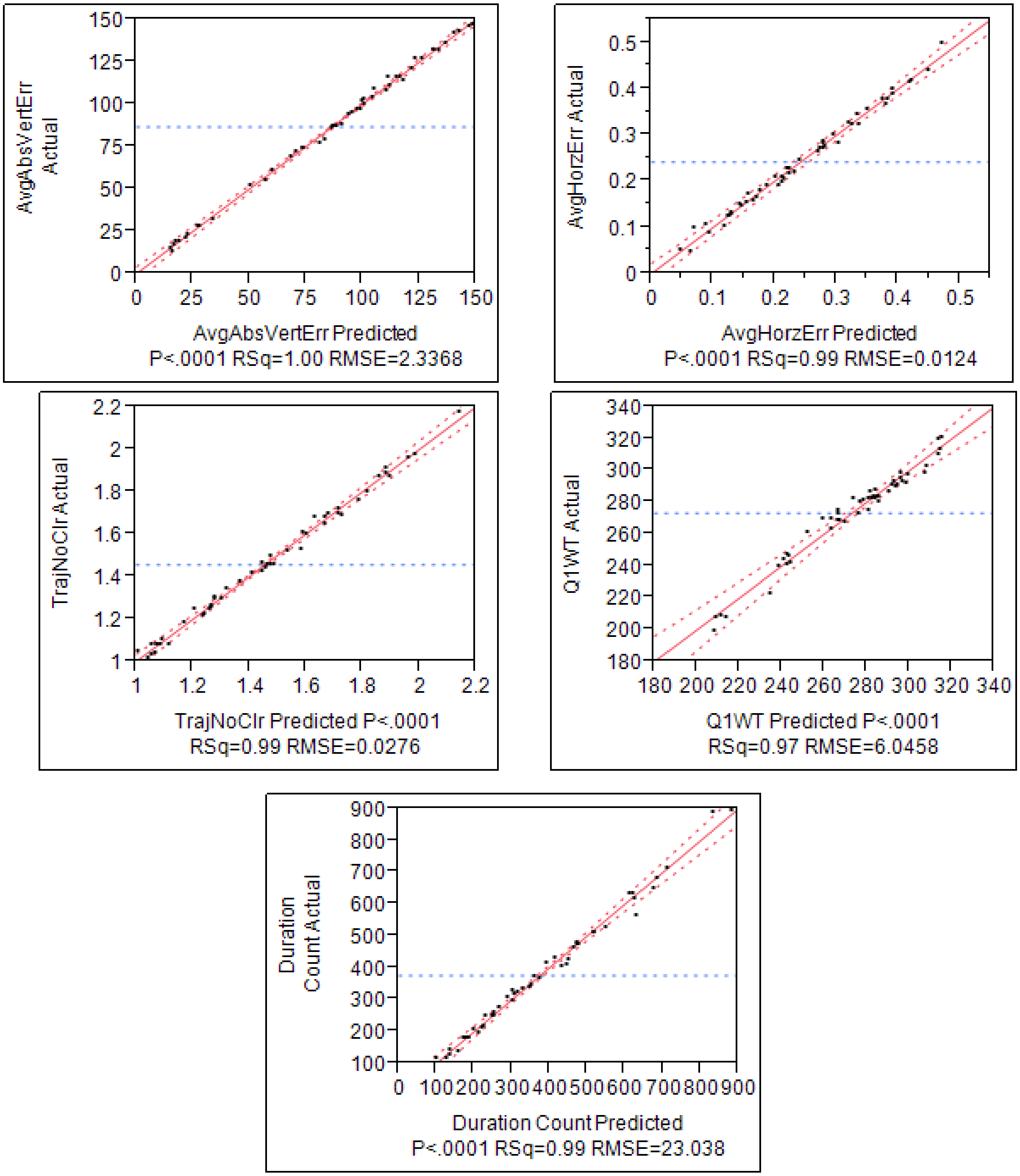

Figure 10: Leverage Plots per Response

Tables 7-11 list the effect tests for the various factor level combinations of the experiment. The intent level is a continuous factor that may have non-linear effects while the others all represent fixed effects. The column labeled “Source” defines the particular effect produced from the combinations of factors listed. The column labeled “DF” is the degrees of freedom for the particular factor combination. The column labeled “Sum of Squares” is calculated by summing the squared differences of the observations minus the mean. The column labeled “F Ratio” is the test statistic produced by model mean square divided by the error mean square. The column labeled "*p*-value" is the probability that the test statistic is not significant. A *p*-value that is less than 0.05 is marked by an asterisk to indicate it provides evidence that the particular factor is statistically significant.

Table 7: Model Effect Tests for Average Horizontal Error

Source	DF	Sum of Squares	F Ratio	*p*-Value
Intent%	1	0.12746576	832.8155	<.0001*
ARTCC	4	0.11483390	187.5709	<.0001*
Traffic Year	1	0.00651133	42.5427	<.0001*
Intent%*ARTCC	4	0.02748042	44.8868	<.0001*
Intent%*Traffic Year	1	0.00242900	15.8702	0.0004*
ARTCC*Traffic Year	4	0.00760976	12.4299	<.0001*
Intent%*Intent%	1	0.00000131	0.0086	0.9267

Table 8: Model Effect Tests for Average Absolute Vertical Error

Source	DF	Sum of Squares	F Ratio	P-Value
Intent%	1	6058.225	1109.408	<.0001*
ARTCC	4	30930.359	1416.025	<.0001*
Traffic Year	1	371.661	68.0601	<.0001*
Intent%*ARTCC	4	1755.926	80.3882	<.0001*
Intent%*Traffic Year	1	72.955	13.3599	0.0009*
ARTCC*Traffic Year	4	103.784	4.7513	0.0039*
Intent%*Intent%	1	70.119	12.8405	0.0011*

Table 9: Model Effect Tests for Response Variable TrajNoClr

Source	DF	Sum of Squares	F Ratio	P-Value
Intent%	1	1.7607103	2317.748	<.0001*
ARTCC	4	0.0991183	32.6191	<.0001*
Traffic Year	1	0.0360800	47.4946	<.0001*
Intent%*ARTCC	4	0.1171211	38.5437	<.0001*
Intent%*Traffic Year	1	0.0158811	20.9054	<.0001*
ARTCC*Traffic Year	4	0.0112091	3.6888	0.0137*
Intent%*Intent%	1	0.0037736	4.9675	0.0328*

Table 10: Model Effect Tests for Response Variable Q1WT

Source	DF	Sum of Squares	F Ratio	P-Value
Intent%	1	10432.901	285.4311	<.0001*
ARTCC	4	6417.190	43.8916	<.0001*
Traffic Year	1	25.205	0.6896	0.4123
Intent%*ARTCC	4	2834.403	19.3864	<.0001*
Intent%*Traffic Year	1	45.901	1.2558	0.2705
ARTCC*Traffic Year	4	145.833	0.9974	0.4228
Intent%*Intent%	1	1477.125	40.4123	<.0001*

Table 11: Model Effect Tests for Response Variable DurationCount

Source	DF	Sum of Squares	F Ratio	P-Value
Intent%	1	480592.08	905.5296	<.0001*
ARTCC	4	109485.04	51.5728	<.0001*
Traffic Year	1	164393.78	309.7501	<.0001*
Intent%*ARTCC	4	51098.96	24.0701	<.0001*
Intent%*Traffic Year	1	31612.84	59.5648	<.0001*
ARTCC*Traffic Year	4	6461.92	3.0439	0.0306*
Intent%*Intent%	1	24182.86	45.5652	<.0001*

The results in Table 7 through Table 11 indicate that all of the main factors had a statistically significant effect according to the fitted model, with the exception of traffic year (and its possible interactions) on predicted warning time. Furthermore, the effect of intent level is found to be non-linear for all response variables, with the exception of horizontal error, for which intent has a fixed, linear effect.

The model assumes that the unattributed variation or error in the model, referred to as random error, $\varepsilon_{n(ijk)}$ in Equation 1 is approximately normally distributed. An additional validation of the model is to test the residuals for normality. These residual errors are presented for each of the five response variables in histograms overlaid with fitted normal distribution density lines, box plots, and normal probability plots for each response variable. Figure 11 depicts residuals for Avg. Abs. Vertical Error, Avg. Horizontal Error, and Trajectory Count (of trajectories not matched to a clearance). Figure 12 depicts residual errors for the 1st quartile of predicted warning time (Q1WT) and the count of alerts with duration greater than 1 minute.

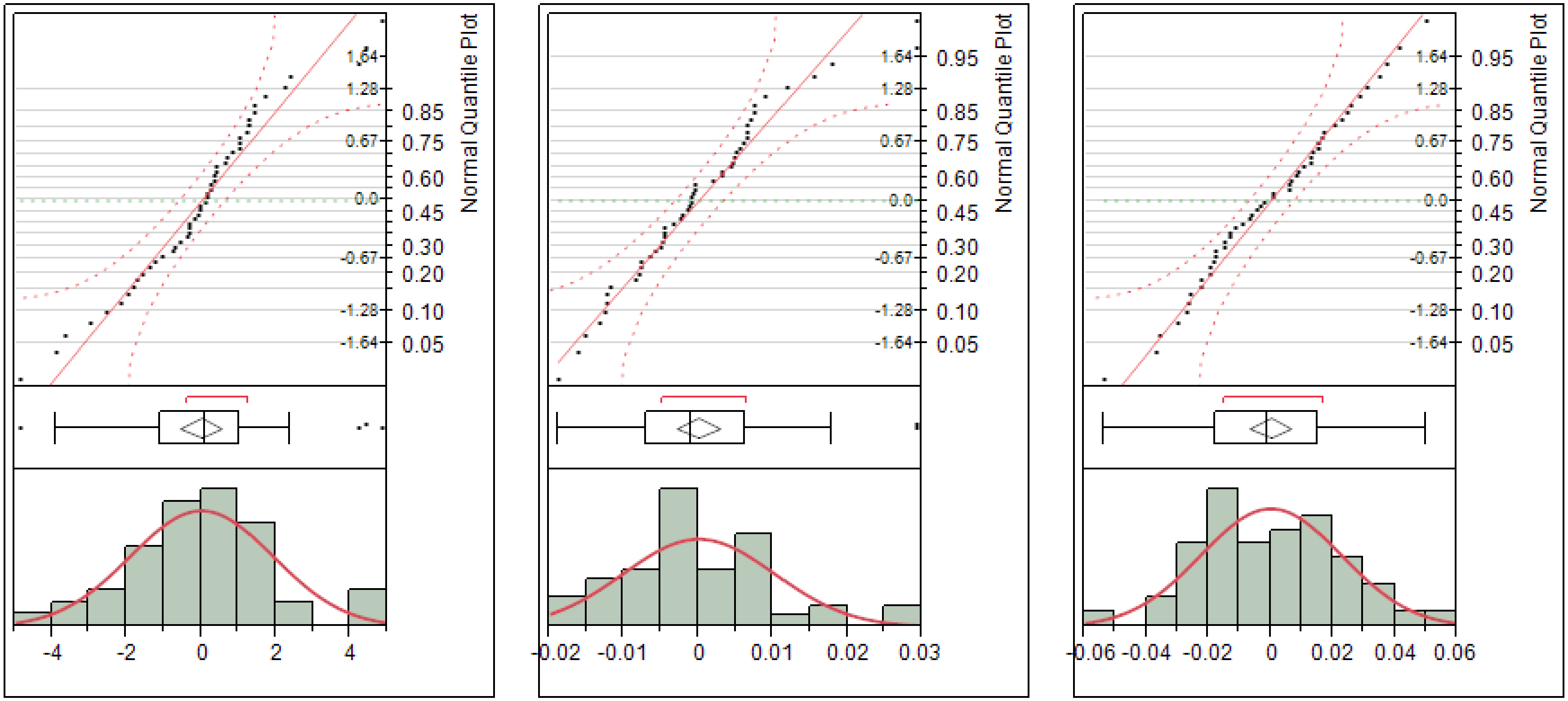

Figure 11: Residual Error Distributions for AAVE, AAHE, and Trajectory Count

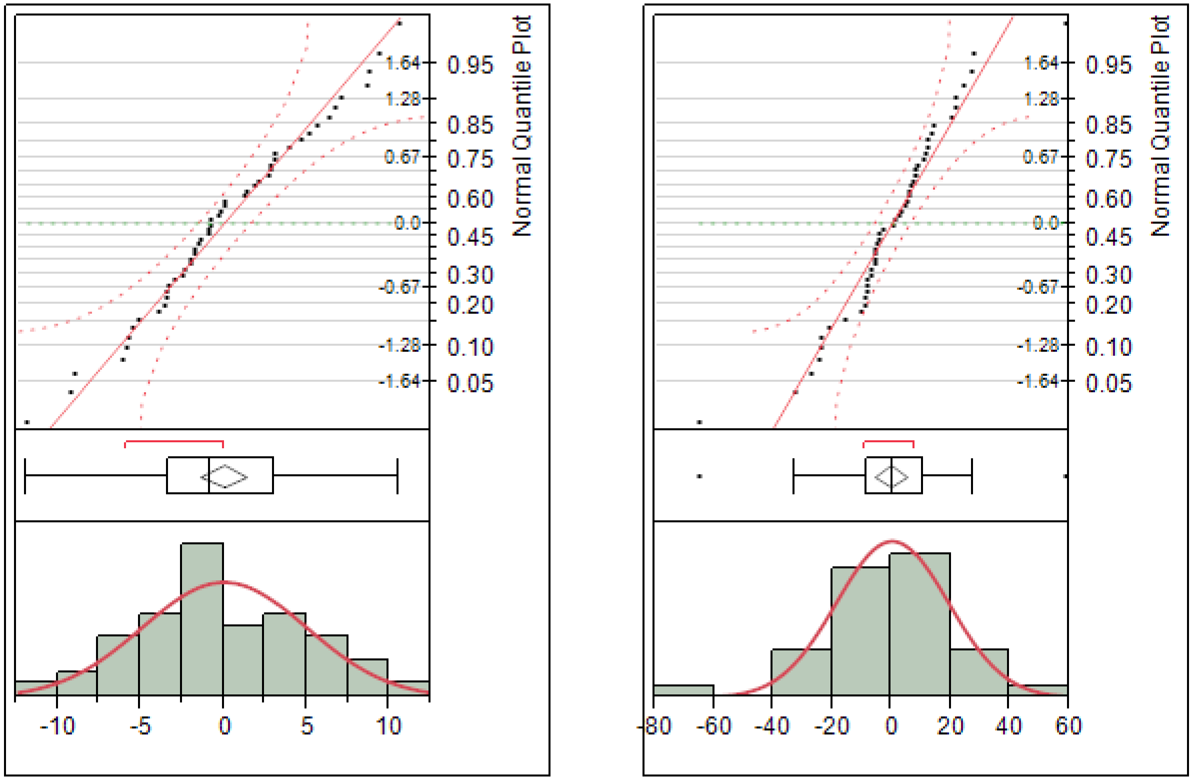

Figure 12: Residual Error Distributions for Q1WT and Duration Count

The histograms and box plots illustrate that the distributions are fairly symmetric and centered at zero as expected if normally distributed. The normal probability plot illustrates for each response that the model errors fall along the diagonal probability line, indicating that each is at least approximately normally distributed and supporting the validity of the model.

The experimental results produce a statistical model with coefficient estimates that are summarized in Table 12. This model allows us to draw conclusions on the relationships and net effects of the various factors under study.

Table 12: Summary of Model Coefficient Estimates

Source	Avg Horz Err (NM)	Avg Abs Vert Error (ft)	Trajectory (No Clr.) Count	Duration Count	Q1 of Warning Time (s)
Intercept	0.3306828	104.47396	1.7937376	488.27429	251.47643
Intent%	-0.00202	-0.440299	-0.007506	-3.9216	0.5778
ARTCC[ZAU]	0.042936	29.282419	0.0434468	123.52	-17.47
ARTCC[ZMA]	-0.027607	18.06752	-0.012748	-61.88	0.48
ARTCC[ZNY]	0.0960769	28.097564	0.0284487	-45.28	-14.07
ARTCC[ZLA]	-0.006081	-11.58431	0.0576475	9.52	3.33
ARTCC[ZDV]	-0.105325	-63.86319	-0.116794	-25.88	27.73
Traffic Year[2025-2018]	0.0228234	5.4527832	0.0537252	114.68	-1.42
(Intent%-50)*ARTCC[ZAU]	-0.000336	-0.111645	-0.000517	-0.9392	0.2611
(Intent%-50)*ARTCC[ZMA]	0.0005096	-0.156627	0.0003695	0.9768	-0.2539
(Intent%-50)*ARTCC[ZNY]	0.0001415	-0.018189	0.0004878	0.4568	0.2191
(Intent%-50)*ARTCC[ZLA]	-0.001094	-0.033004	-0.002252	-1.2272	-0.0119
(Intent%-50)*ARTCC[ZDV]	0.0007796	0.3194645	0.0019119	0.7328	-0.2144
(Intent%-50)*Traffic Year[2025-2018]	-0.000394	-0.068331	-0.001008	-1.4224	0.0542
ARTCC[ZAU]*Traffic Year[2025-2018]	-0.014156	-2.243095	-0.030131	-14.68	4.97
ARTCC[ZMA]*Traffic Year[2025-2018]	-0.001887	-1.673652	-0.003673	4.12	-3.48
ARTCC[ZNY]*Traffic Year[2025-2018]	-0.014235	1.5012082	-0.027379	-32.88	2.02
ARTCC[ZLA]*Traffic Year[2025-2018]	0.0481462	4.983336	0.0522818	34.52	-4.13
ARTCC[ZDV]*Traffic Year[2025-2018]	-0.017868	-2.567797	0.0089017	8.92	0.62
(Intent%-50)*(Intent%-50)	1.5501e-7	0.0011323	8.3068e-6	0.0210286	-0.005197

The results in Table 12 can be interpreted by comparing the size of the effects to the intercept, which is the mean response value over all levels. For every one percent increase in intent entered, the average horizontal error decreases by 0.002NM and average absolute vertical error by -0.44 ft. The number of trajectories per flight decreases by 0.0075 for every percent increase in intent entry, compared to the 1.7937 overall average. The count of alerts with duration greater than one minute decreases by roughly 3.92 on average per one percent increase. This is compared to the intercept value of 488 total long duration alerts. The first quartile of predicted warning time increases by 0.5778 seconds for every increase of one percent intent entry. Comparing no intent entry (0%) to full intent entry (100%), therefore, the first quartile increases by roughly one minute. Likewise, the horizontal error decreases by 0.2NM, or 61%; vertical error decreases by 44 ft, or roughly 42% of the general average. The trajectory count per flight decreases by 0.7 from minimum to maximum intent entry, which is 42%. And the count of alerts with long duration decreases by 392, or 80% of the intercept value.

The JMP® commercial software tool provides an interactive model calculator called the predictor profiler that allows the examination of the effects of the various factors of the model[5]. Figure 13 presents the predictor profile plot of the model results. The general trend is that year has a negligible effect on all

5 For details on the JMP® software tool and the predictor profiler see www.jmp.com.

responses except the count of alerts with long duration. The choice of ARTCC has the largest effect on the average of the absolute vertical errors. Increasing the intent level also displays desirable effects in the model: average horizontal and vertical error decrease, the count of trajectories with no associated clearance decreases, the count of alerts with long duration decreases, and the predicted warning time increases. These trends show that the model agrees with the hypothesis that increased intent in the system produces a positive effect.

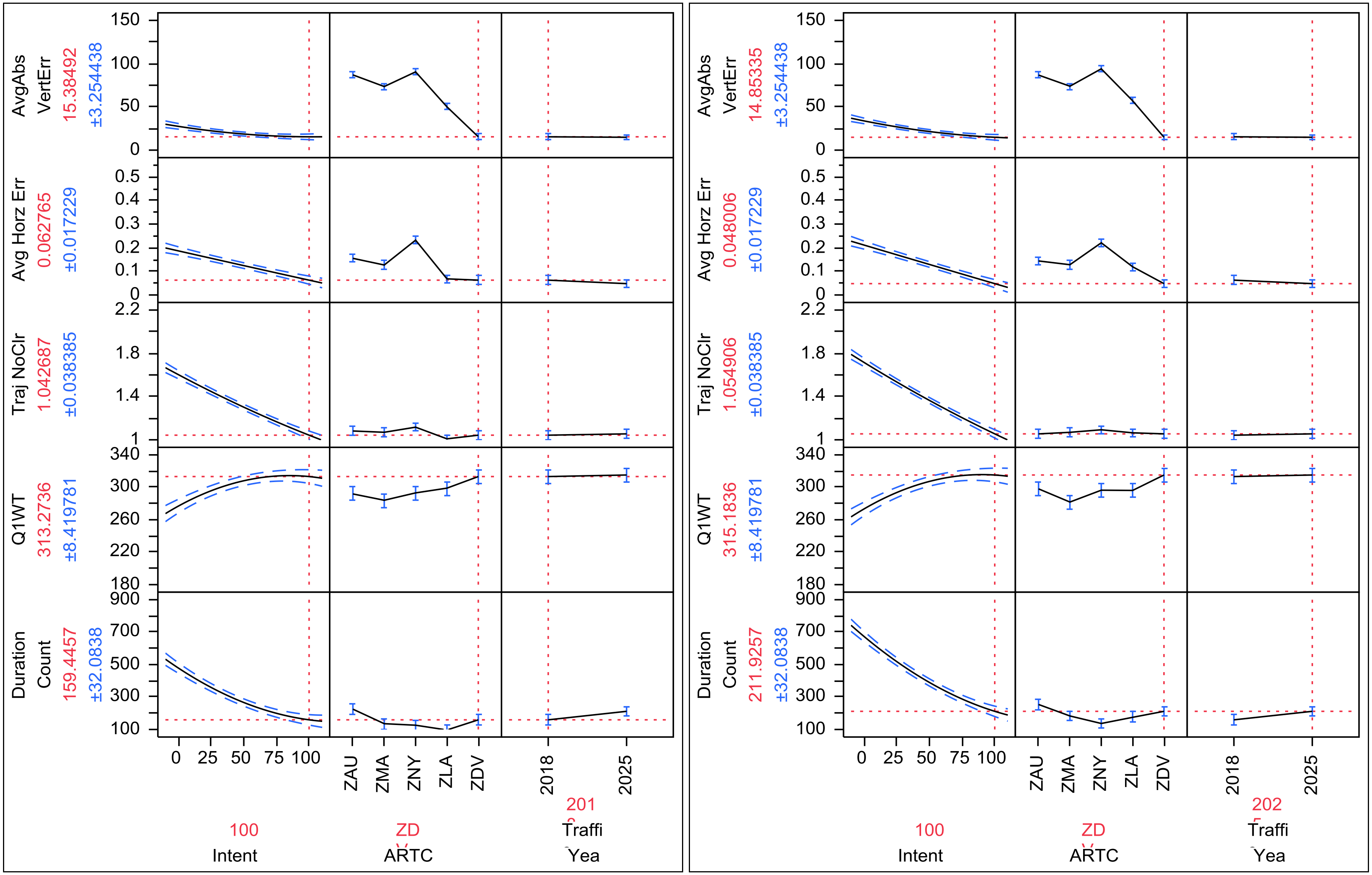

Figure 13: Predictor Profiler for 2018 (left) and 2025 (right)

The slopes of the plotted lines in Figure 13 indicate the magnitude and direction of each factor's effect on the model. The curvature in the intent factor indicates its non-linear effects which are stronger at low intent levels. The y-axis plots the response variable estimates from the model and the decimal numbers on each y-axis represents the modeled response variable at the levels specified in the figures. The setting chosen for the profiler graphics are the ZDV ARTCC, at full (100%) intent for both years. ZDV is chosen because it demonstrates the greatest positive benefits.

3.4 Flight Examples

This section presents three example conflicts that are selected to demonstrate how the trajectory modeling and conflict probe alert performance vary with intent level. Instances are identified in a reduced intent scenario in which intent is not sent to the ground automation system. Each example follows one such instance in the reduced intent scenario and compares it to the same time in the associated full intent scenario. Relevant trajectory information and conflict alert information are presented. The paths of the flights involved are depicted from each scenario to show the effect of improved intent.

The examples attempt to capture a wide array of benefit mechanisms from improved intent entry. The first scenario is 2018 traffic in Chicago center (ZAU) with low intent entry (that is, with 25% of 2-part clearances entered). This low-intent scenario is compared to the full intent scenario (with all clearances fully entered) for ZAU 2018 traffic. The FAA FliteViz4D visualization tool [2] is used to explore the scenario data and produce the graphics in the following examples.

Please note this section presents simulations of aircraft encounters. While the flight trajectories are representative of real trajectories that could have been generated by the ground automation system, the track data are entirely fabricated and in no way reflect actual encounters that took place. The flight names used in the examples may reflect actual call signs used in operations, but the reader is cautioned that they are computer generated for this experiment only and do not reflect real flights.

3.4.1 Example 1 – False Alert Induced by Reduced Intent Amendment

The first example involves Flight JBU921, an Embraer 190 aircraft flying from Boston Logan airport to Chicago O'Hare airport, with the intermediate fixes EMMMA, WYNDE, ERNNY, and RAPPI. Flight UAL327 is a Boeing 757 aircraft flying from LaGuardia airport in New York to Chicago O'Hare airport, with the intermediate fixes COATE, MINEO, GOOSS, EMMMA, WYNDE, ERNNY, and RAPPI, as depicted in Figure 14. The cruise altitudes are FL360 for JBU921 and FL380 for UAL327. The encounter duration between the aircraft starts at 49190 seconds and ends at 49340 seconds.

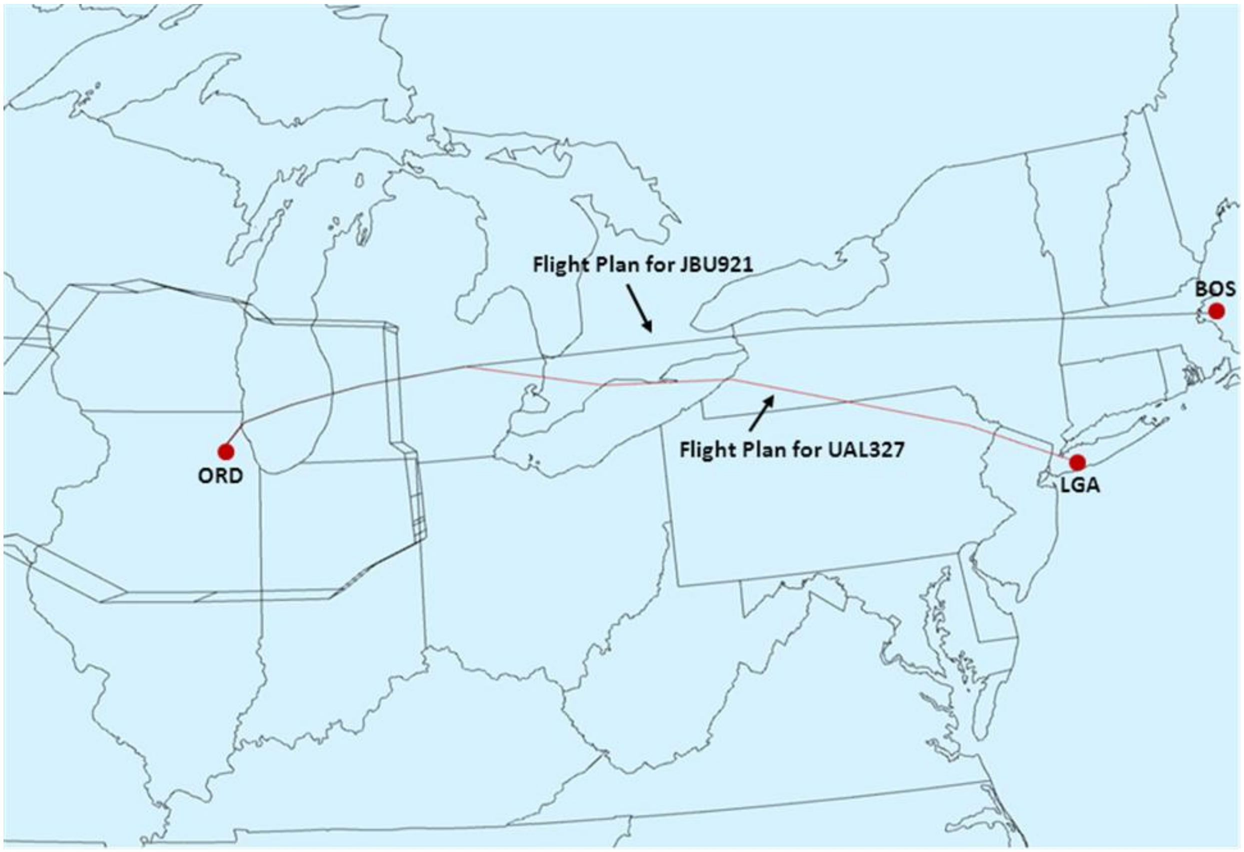

Figure 14: Flight Paths for the Conflicting Aircraft

A conflict is predicted between these two aircraft to occur at 49266 seconds and the notification time of the conflict is 48881 seconds. The minimum horizontal and vertical separations for the predicted conflict are 4.41 nautical miles and 993 feet respectively. A two-part lateral resolution maneuver for JBU921 is issued to resolve the conflict without intent entry, JBU921 starts the maneuver at 49195 seconds, and UAL327 starts to descend at 49234 seconds. Without the knowledge of the resolution intent, the trajectory predictor (TP) assumes a shorter outbound distance with which the conflict probe (CP) predicts a false conflict between JBU921 and UAL327 to occur at 49246 seconds, as depicted in Figure 15 and Figure 16. The conflict prediction is made when JBU921 reaches the actual position of (x=592.76, y=435.00, z=36000) and UAL327 reaches (x=592.56, y=420.18, z=37987), where x and y are the perpendicular distances in NM to some fixed point of reference, and z is the altitude in feet. The conflict is predicted to occur at 3 minutes into the future of the aircraft being at these positions. The headings used for the prediction are 273 degrees for JBU921 and 258 degrees for UAL327, and the speeds used for the prediction are 453 knots for JBU921 and 462 knots for UAL327. The minimum horizontal and vertical separations for the falsely predicted conflict are 3.57 nautical miles and 15 feet respectively.

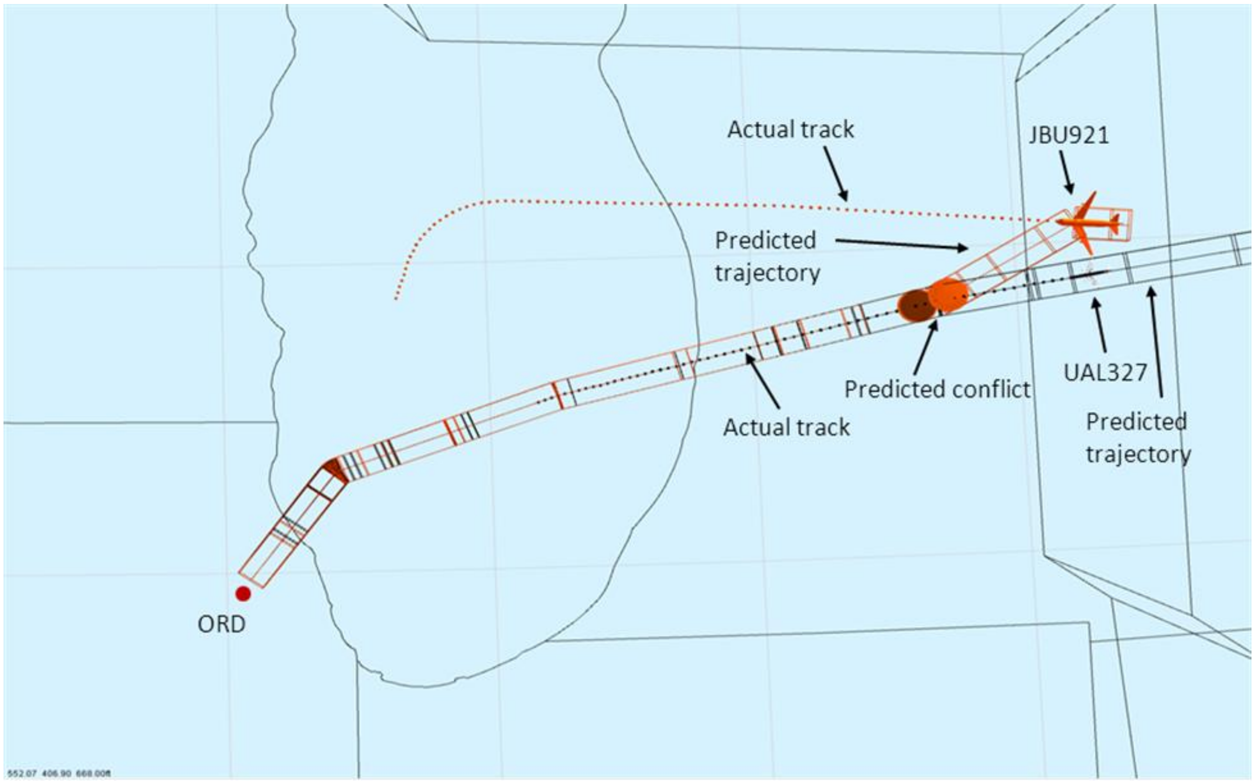

Figure 15: Horizontal Visualization of the Conflict Resolution without Intent Entry

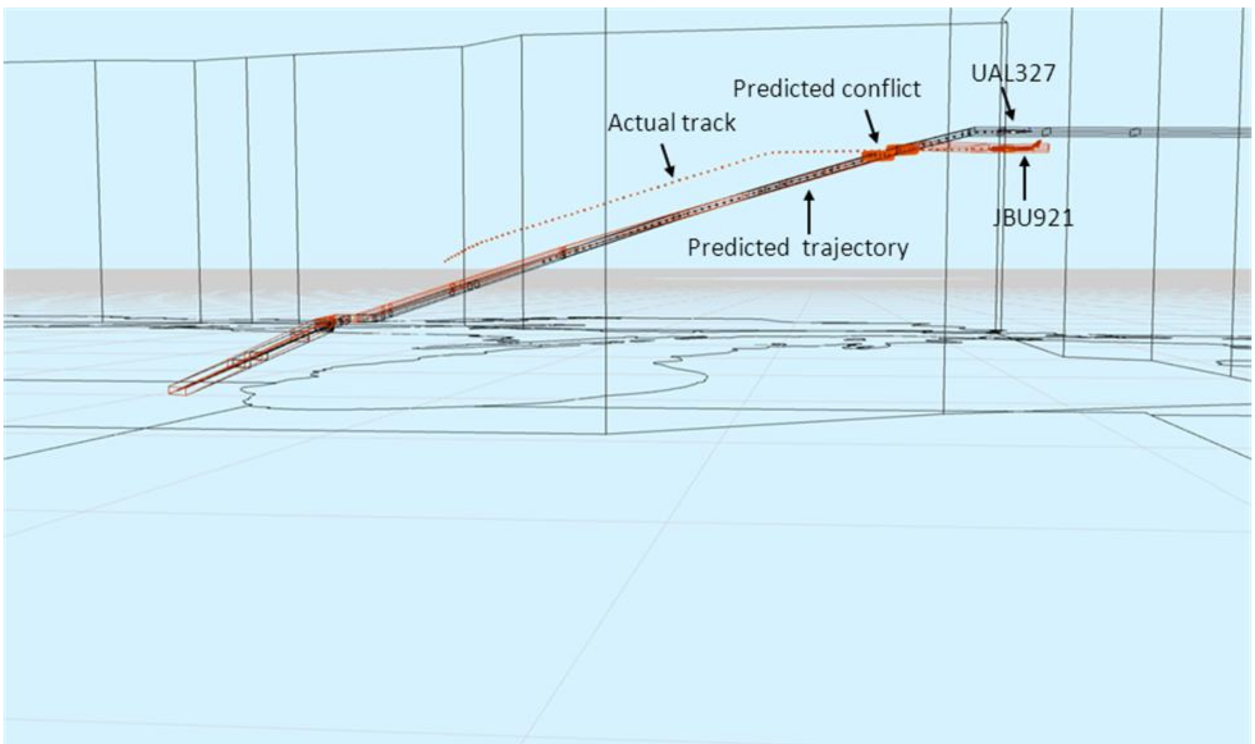

Figure 16: Vertical Visualization of the Conflict Resolution without Intent Entry

When the resolution maneuver is issued with intent entry, the TP models the exact outbound distance and the resulting trajectories are conflict free, as depicted in Figure 17 and Figure 18.

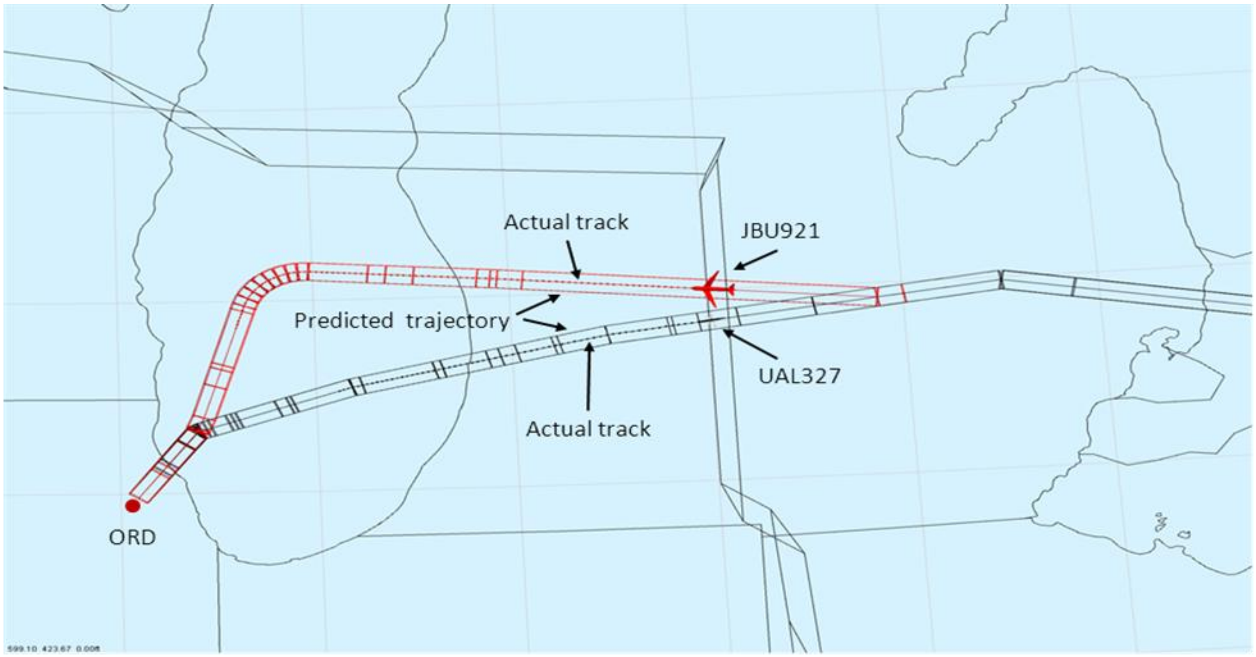

Figure 17: Horizontal Visualization of the Conflict Resolution with Intent Entry

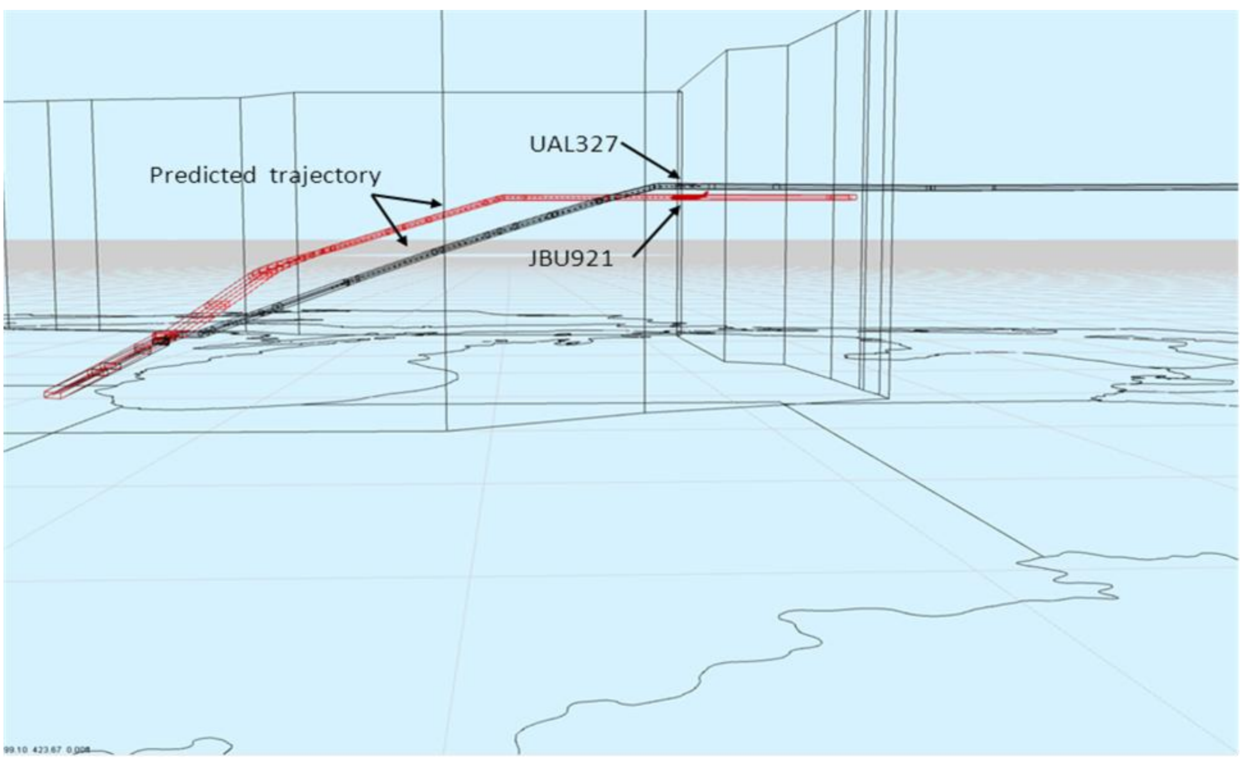

Figure 18: Vertical Visualization of the Conflict Resolution with Intent Entry

So, when the 2-leg maneuver for JBU921 is not entered into the ground automation system, the modeled trajectory is incorrect. Due to this lack of intent information, the conflict probe generates an alert for a predicted conflict which does not occur. In contrast, when the full clearance for JBU921 is entered into the ground automation the trajectory is modeled correctly, and no false alert is produced.

3.4.2 Example 2 – Late Alert due to Reduced Intent Amendment

The second example in ZAU involves Flight PAT128, a Fairchild Metro-Merlin 4 aircraft flying from Columbia Metropolitan airport in South Carolina to La Crosse Municipal airport in Wisconsin, with the intermediate fixes SPA, BMG, DNV and SIBER. Flight SWA107 is a Boeing 737 aircraft flying from Midway airport in Chicago to LAX International airport in Los Angeles, with the intermediate fixes SIMMN, MZV, ALBRT, JAVAS, LMN, COCAN, BUGGA, EMMEY, and CIVET, as depicted in Figure 19. The cruise altitudes are FL200 for PAT128 and FL400 for SWA107. SWA107 implements a step climb at 54540 seconds for which the full amendment is not entered into the automation system. The encounter duration between the aircraft starts at 55400 seconds and ends at 55540 seconds.

Figure 19: Flight Paths for the Conflicting Aircraft

A conflict is predicted between these two aircraft to occur at 55391 seconds and the notification time of the conflict is 55008 seconds. The minimum horizontal and vertical separations for the predicted conflict are 2.86 nautical miles and 117 feet respectively. A two-part lateral resolution maneuver is issued for PAT128 to resolve the conflict without intent entry and PAT128 starts the maneuver at 55062 seconds.

This resolution is based on partial intent information for SWA107. After PAT128 performs the resolution maneuver, a conflict is predicted along the resolution trajectory to occur at 55420 seconds between SWA107 and PAT128, as depicted in Figure 20 and Figure 21. The trajectories are predicted when PAT128 reaches (412.77, 348.56, 20000) and SWA107 reaches (415.81, 348.88, 19481) with 1 minute look ahead time. The headings used for the prediction are 282 degrees for PAT128 and 249 degrees for SWA107, and the speeds used for the prediction are 269 knots for PAT128 and 354 knots for SWA107. The minimum horizontal and vertical separations for the predicted conflict are 3.69 nautical miles and 100 feet respectively.

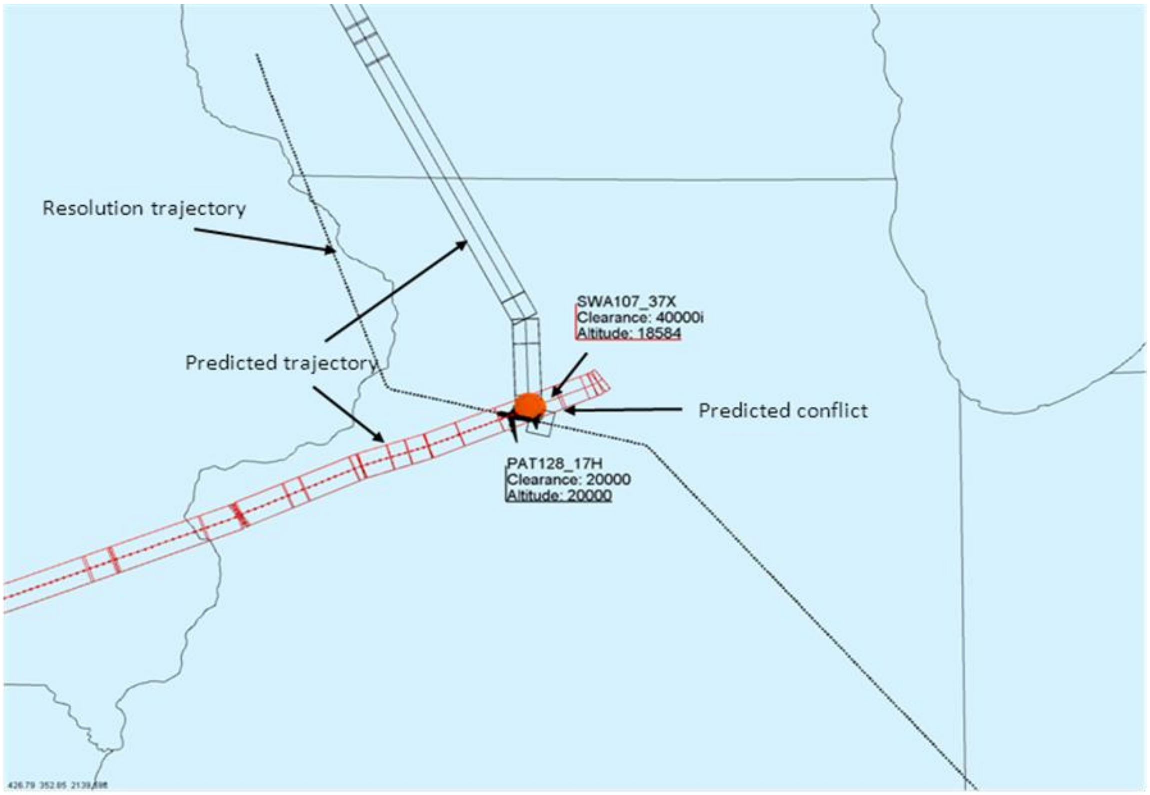

Figure 20: Horizontal Visualization of the Predicted Conflict due to Resolution without Intent Entry

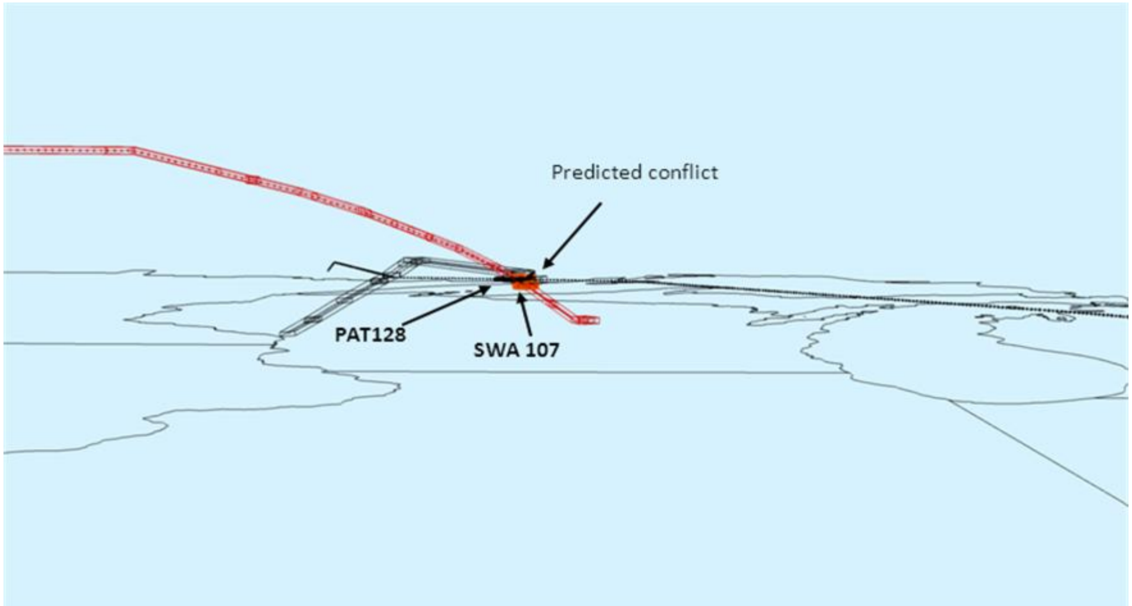

Figure 21: Vertical Visualization of the Predicted Conflict due to Resolution without Intent Entry

However, the loss of separation occurs at 55427 seconds, which makes the 1-minute look ahead conflict prediction a late detection with a seven-second warning time, as depicted in Figure 22 and Figure 23. The loss of separation occurs when PAT128 reaches (417.26, 348.91, 20000) and SWA107 reaches (413.83, 348.08, 19481). The minimum observed horizontal separation is 4.1 nautical miles and the minimum observed vertical separation is 529 feet.

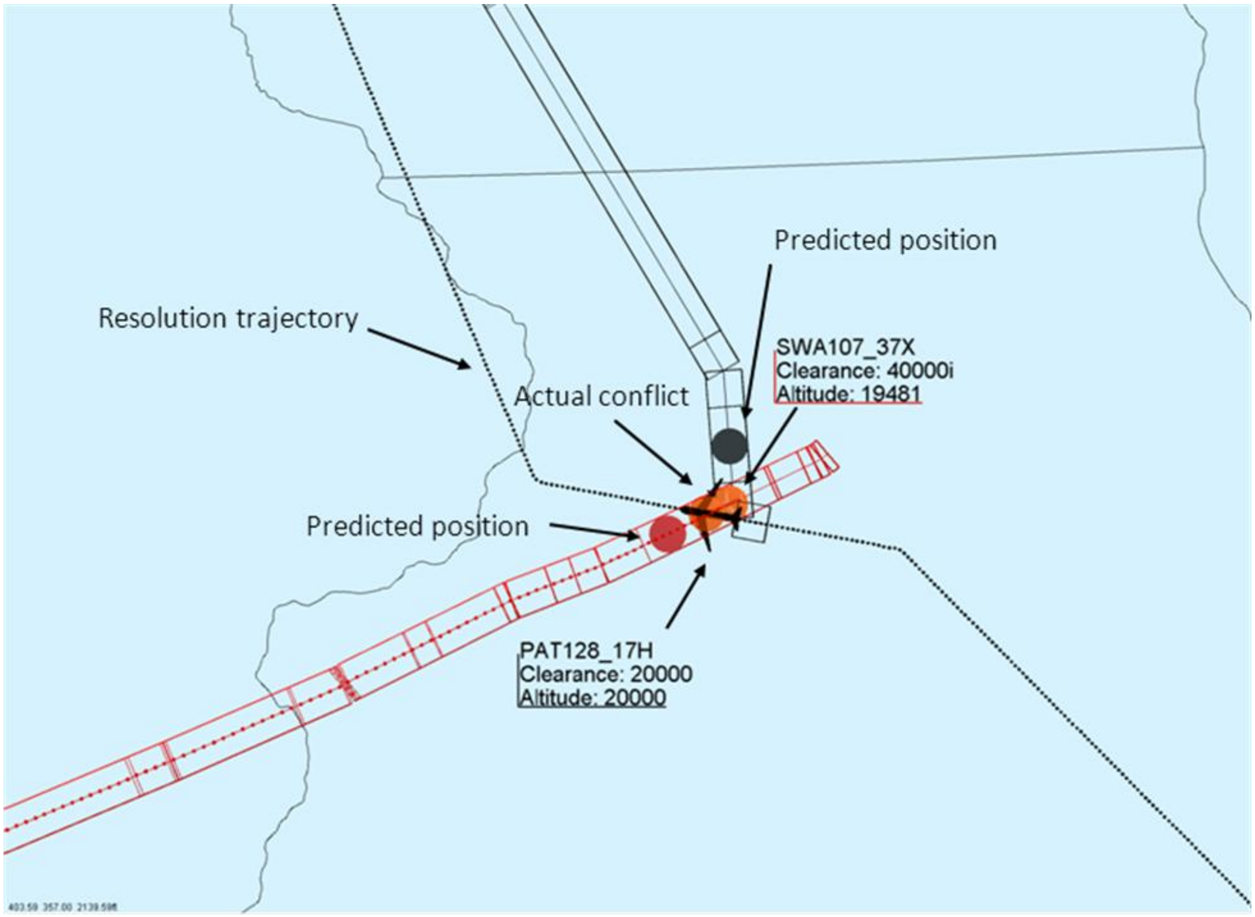

Figure 22: Horizontal Visualization of the Conflict Resulting in a Late Valid Alert

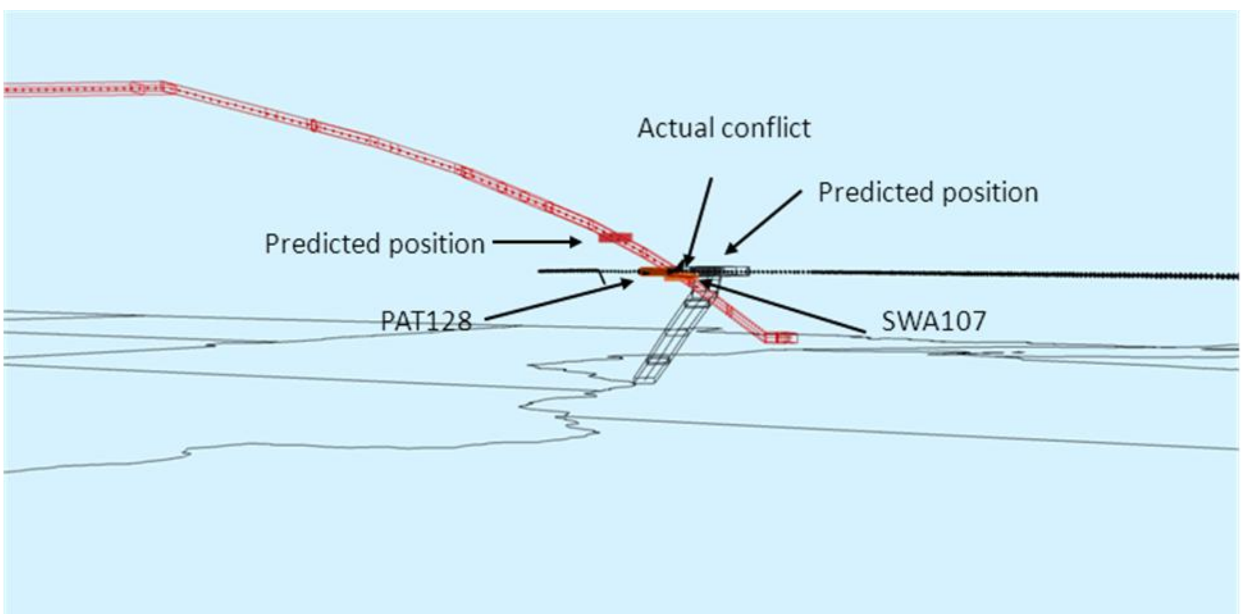

Figure 23: Vertical Visualization of the Conflict Resulting in a Late Valid Alert

When the resolution is issued with intent entry, the TP predicts the trajectories more accurately and the CP does not predict any conflict, as depicted in Figure 24 and Figure 25.

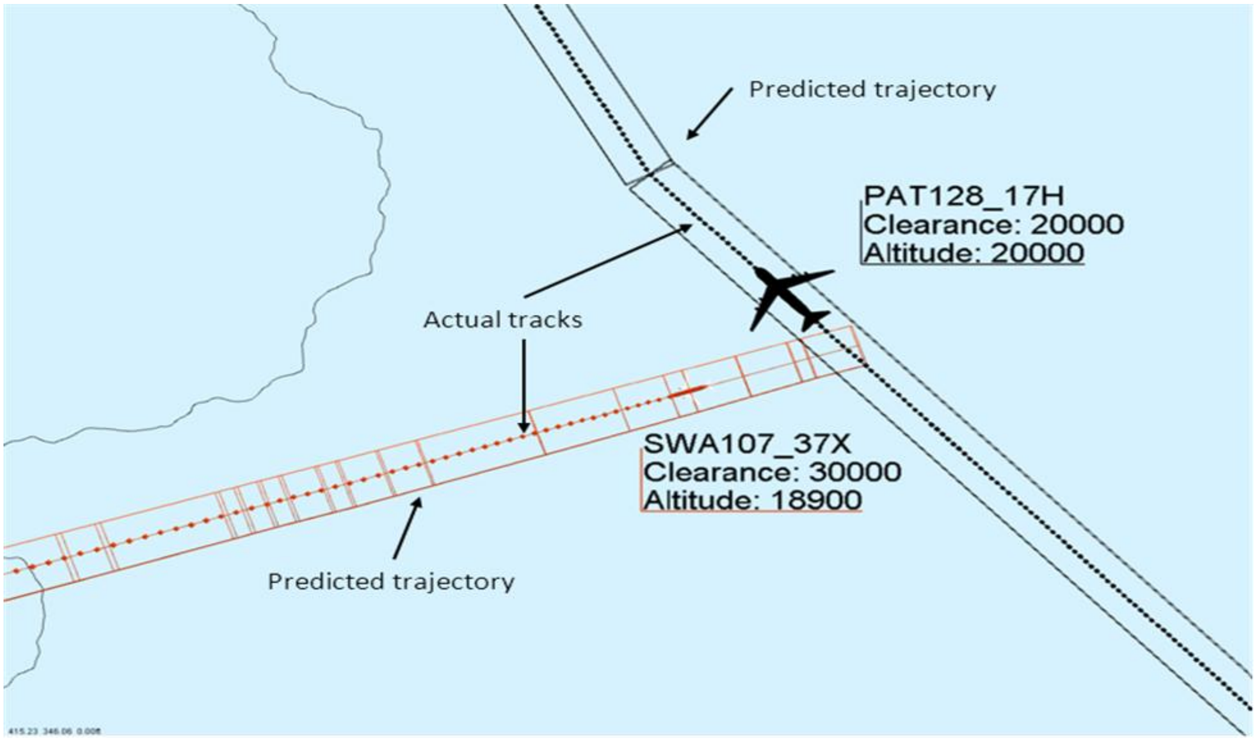

Figure 24: Horizontal Visualization of the Conflict Resolution with Intent Entry

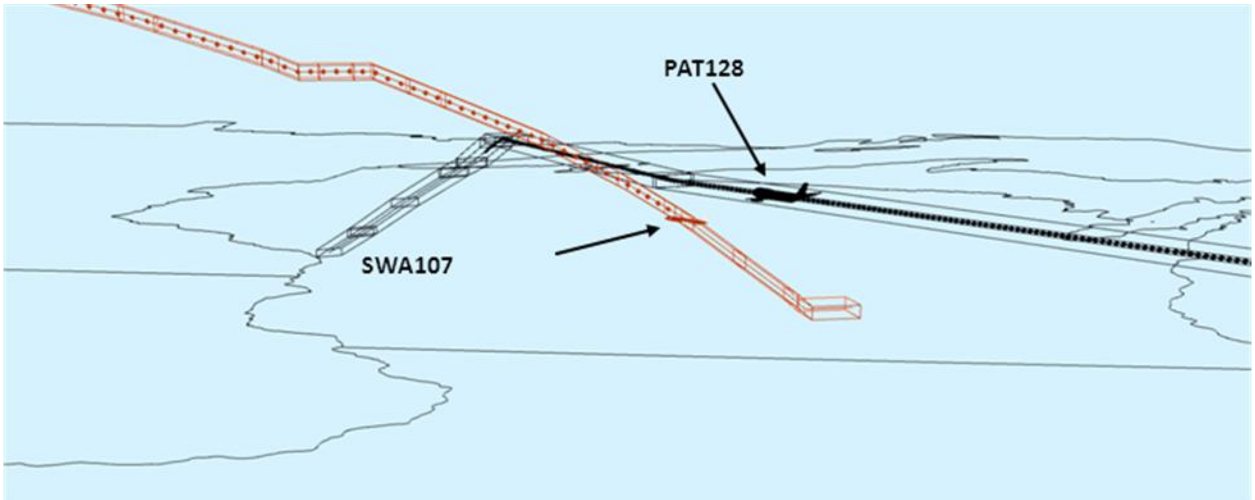

Figure 25: Vertical Visualization of the Conflict Resolution with Intent Entry

When the 2-leg maneuver for PAT128 is not entered into the ground automation system, and an interim altitude is entered for SWA107, the modeled trajectories are incorrect. The lack of intent information causes the conflict probe alert to be late. In contrast, when the full clearances are entered into the ground automation the trajectories are modeled correctly.

3.4.3 Example 3 – False and Missed Alerts due to Multiple Trajectory Rebuilds

The third and last example involves Flight AAL408, a McDonnell Douglas MD-82 aircraft flying from San Antonio International airport in Texas to Chicago O'Hare International airport, with the intermediate fixes HENLY, JUMBO, EDNAS, AKUNA, BENKY and NEWRK. Flight AAL448 is a Boeing 737 aircraft flying from Grove Hill Municipal Airport in Illinois to Chicago O'Hare International airport, with the intermediate fixes BENKY, and NEWRK. Flight UAL397 is a Boeing 757 aircraft flying from McCarran International airport in Las Vegas to Chicago O'Hare International airport, with the intermediate fixes TOMIS, BATIS, NICLE, PWE, IRK, COLIE, LOAMY, BENKY, and NEWRK, as depicted in Figure 26. The cruise altitudes are FL310 for AAL408, FL380 for AAL448, and FL350 for UAL397. The encounter duration for the three aircraft starts at 80580 seconds and ends at 81450 seconds.

Figure 26: Flight Paths for the Conflicting Aircraft

A conflict is predicted to occur between AAL408 and AAL448 at 80887 seconds and the notification time of the conflict is 80558 seconds. The minimum horizontal and vertical separations for the predicted conflict are 4.65 nautical miles and 210 feet respectively. A two-part lateral resolution maneuver is issued for AAL448 to resolve the conflict without intent entry and AAL448 starts the maneuver at 80573 seconds. Aircraft UAL397 deviates from its planned route at 80616 seconds due to an clearance being given but not entered into the automation system. In following this clearance, UAL397 changes its heading from 67 degrees to 105 degrees, while AAL448 is moving toward UAL397's deviated flight path, as depicted in Figure 27.

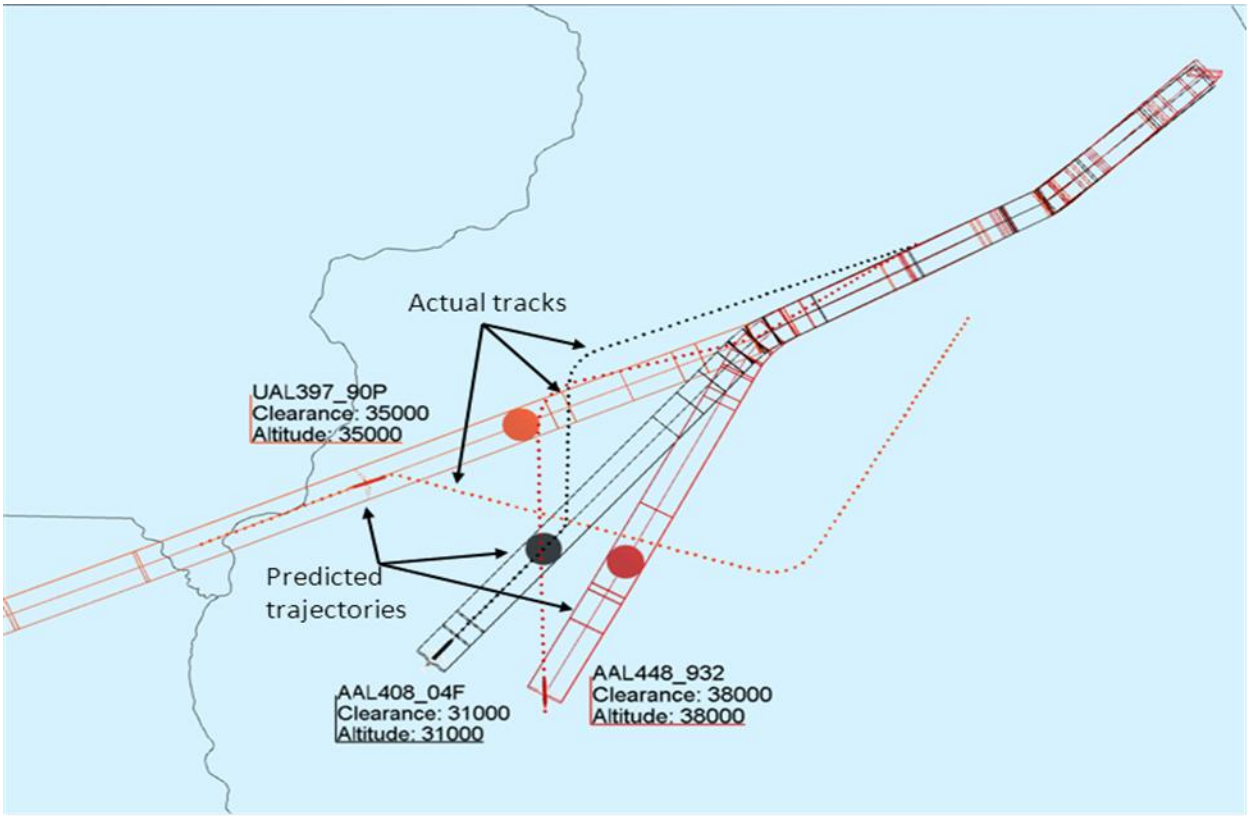

Figure 27: Intersection of the Resolution Flight Path and the Deviated Flight Path

Without the knowledge of the intent of both aircraft, the TP assumes shorter turn out distance for AAL448 and UAL397's original planned path to predict the trajectories for UAL397 and AAL448. As a result, the CP predicts a false conflict between UAL397 and AAL448 to occur at 80772 seconds with predicted minimum horizontal separation of 1.46NM and minimum vertical separation of 150 feet, as depicted in Figure 28 and Figure 29. As the aircraft proceed along the current directions, the CP predicts a false conflict between AAL448 and AAL408 to occur at 80942 seconds using AAL448's trajectory rebuild with shorter turn out distance and AAL408's trajectory along its planned flight path. The horizontal and vertical minimum separations for the predicted conflict are 1.22 nautical miles and 514 feet respectively, as depicted in Figure 30 and Figure 31 .

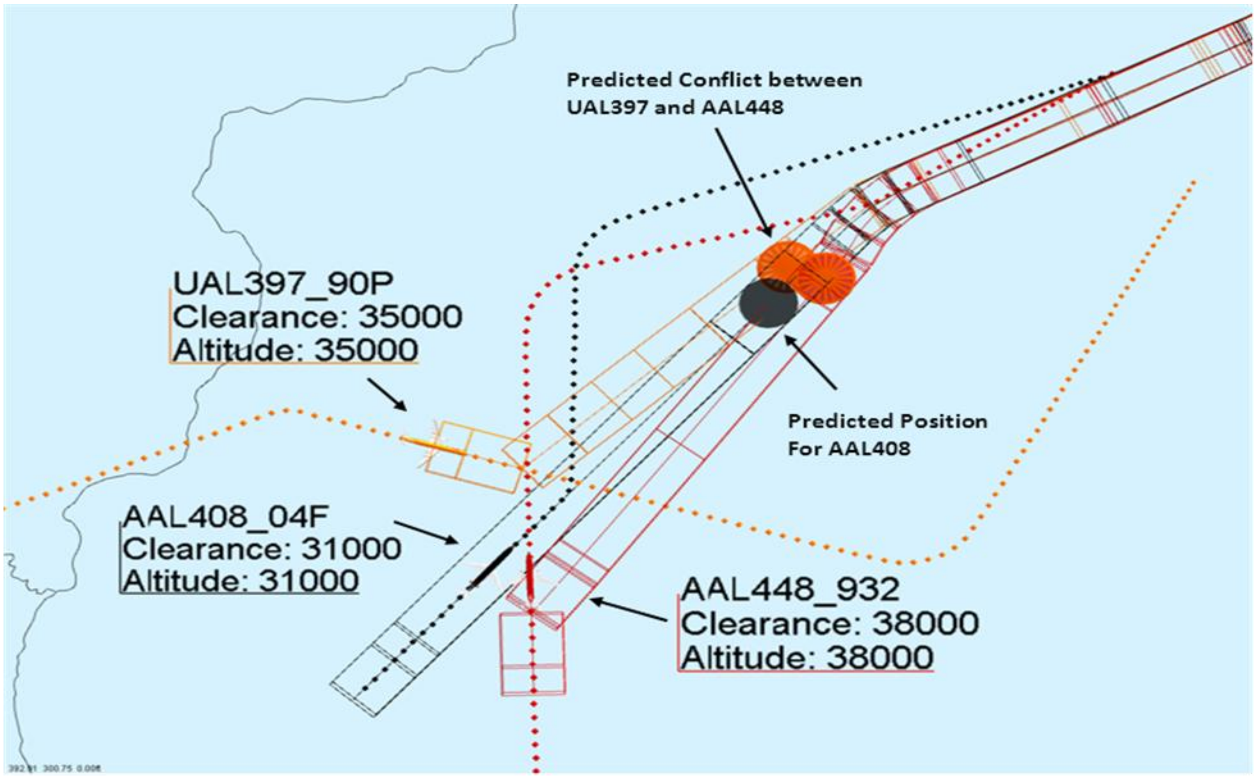

Figure 28: Horizontal Visualization of the Predicted Conflict between UAL398 and AAL448

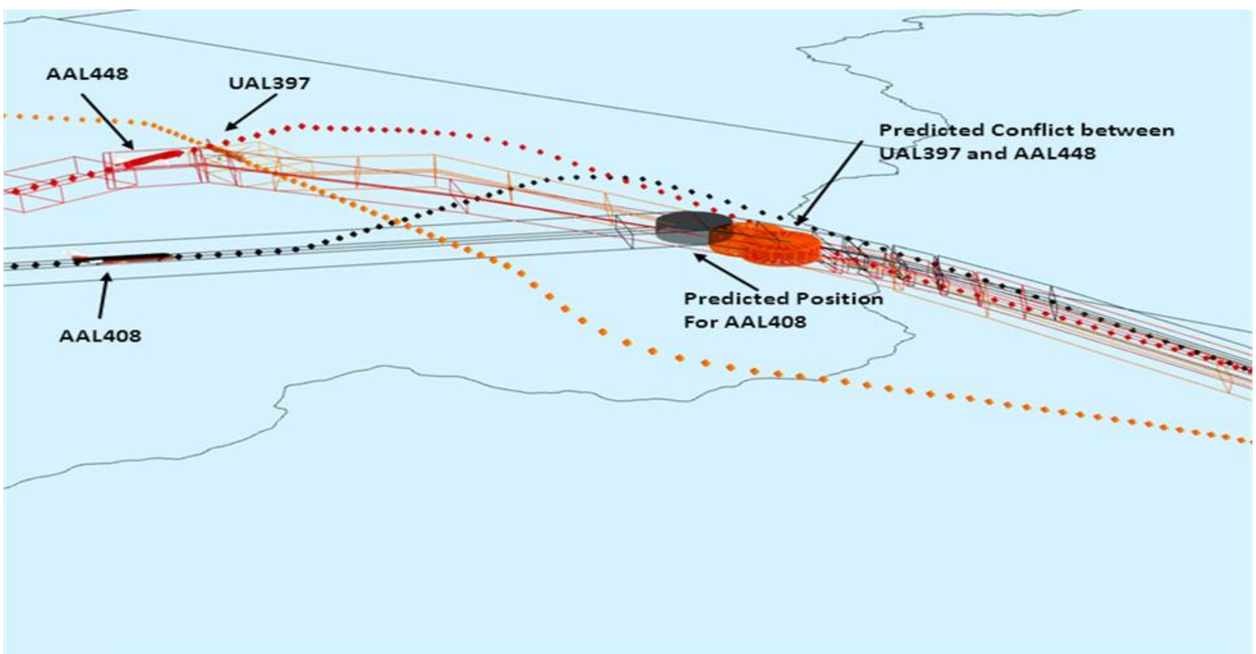

Figure 29: Vertical Visualization of the Predicted Conflict between UAL397 and AAL448

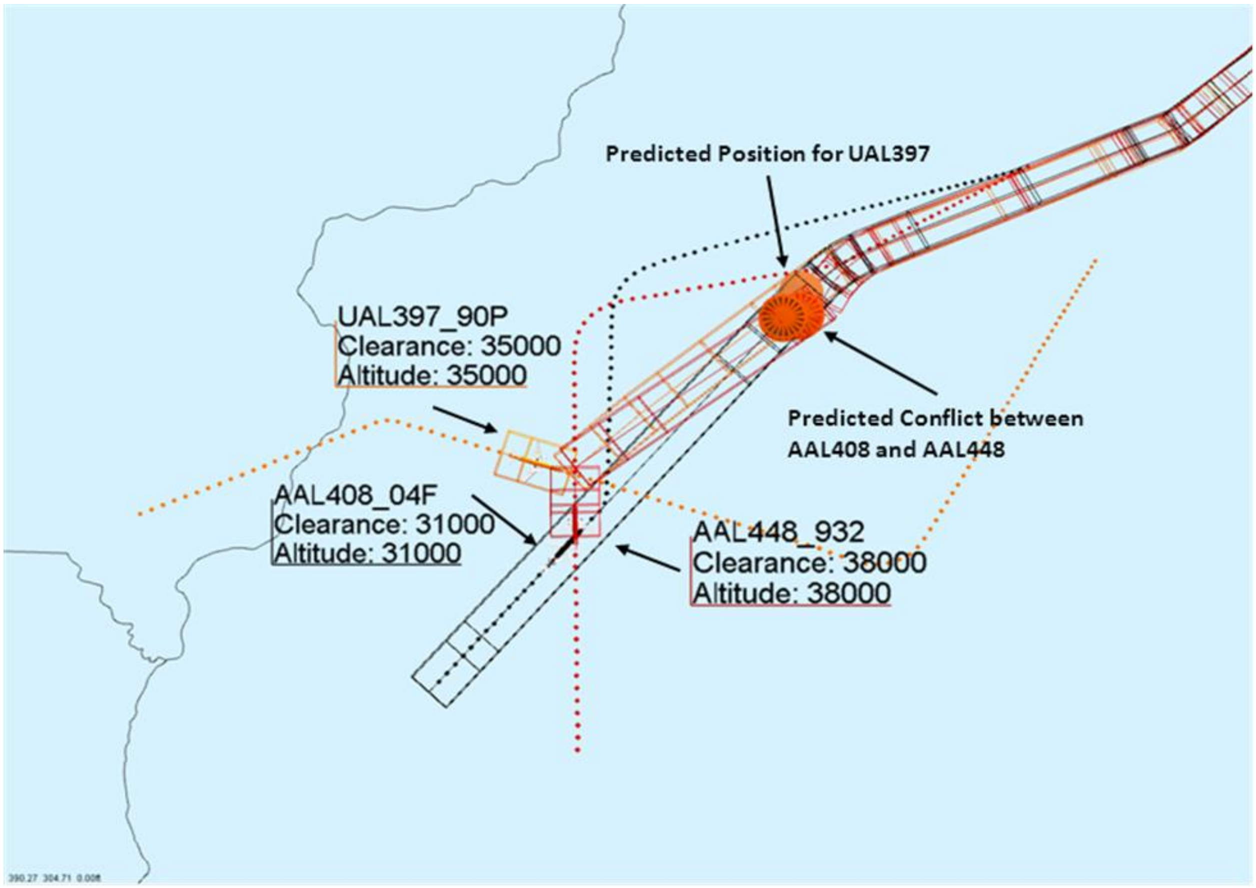

Figure 30: Horizontal Visualization of the Predicted Conflict between AAL448 and AAL408

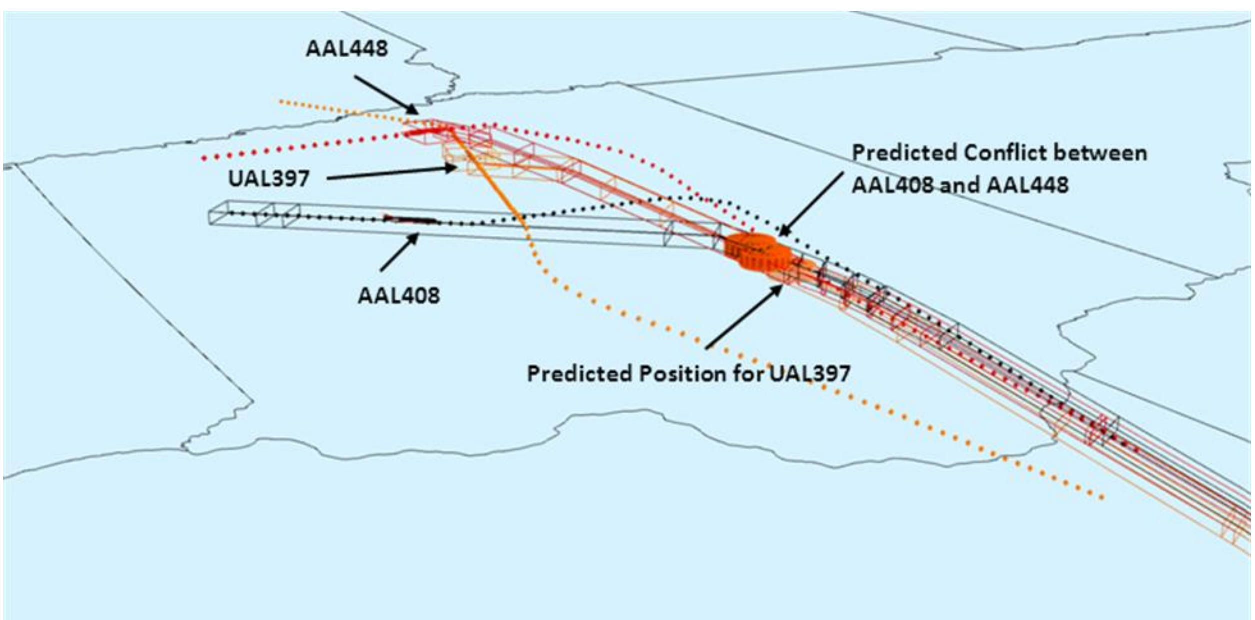

Figure 31: Vertical Visualization of the Predicted Conflict between AAL408 and AAL448

In response to the false alert predicted to occur at 80942 seconds, AAL408 starts to perform the two-part lateral resolution maneuver without intent entry at 80800 seconds, while the CP predicts a conflict between AAL408 and UAL 397 using AAL408's trajectory along its planned flight path and UAL397's trajectory with shorter turn out distance, as depicted in Figure 32 and Figure 33.

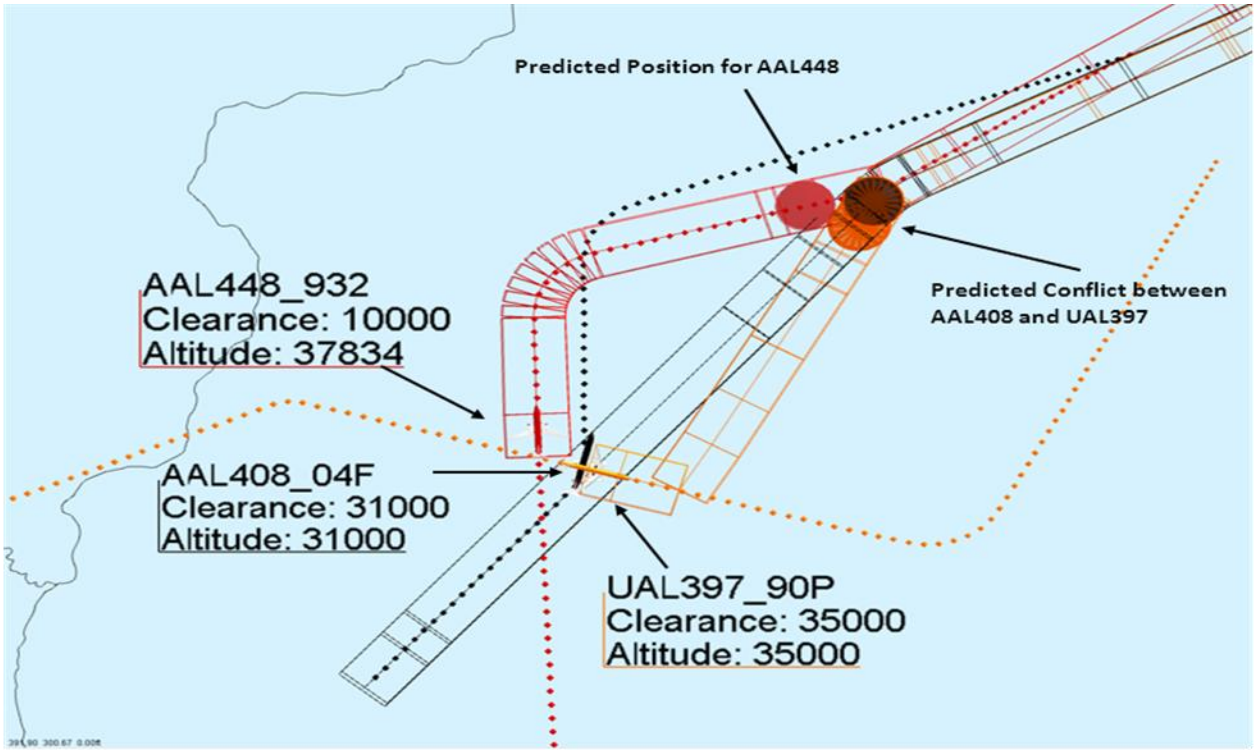

Figure 32: Horizontal Visualization of the Predicted Conflict between UAL397 and AAL408

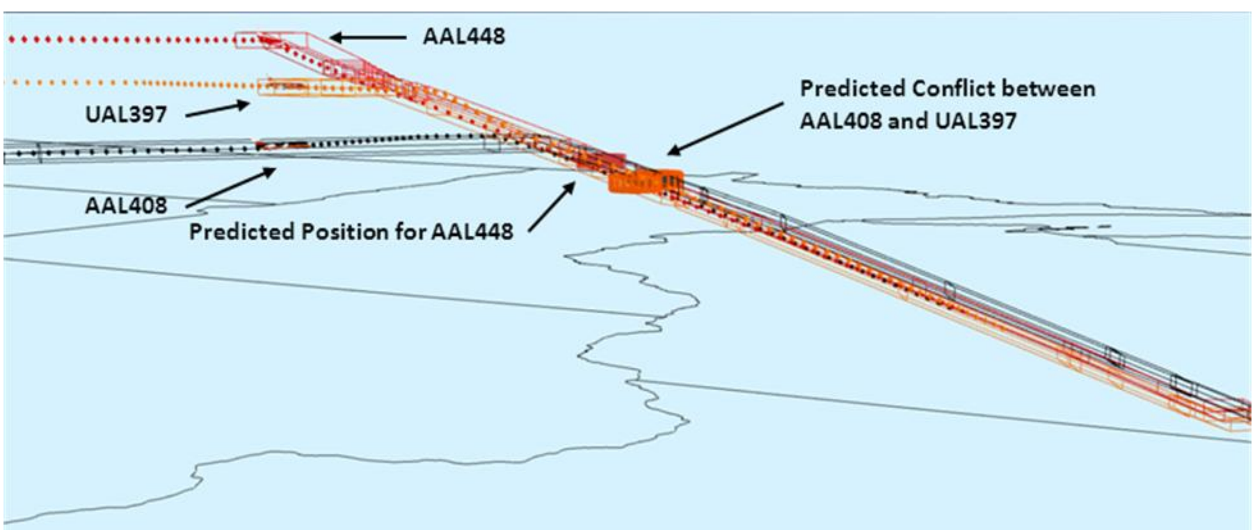

Figure 33: Vertical Visualization of the Predicted Conflict between UAL397 and AAL408

The TP continues to assume the shorter turn out distance to generate the trajectory for AAL408, and the CP predicts a conflict between AAL408 and AAL448 to occur at 81004 seconds with the minimum horizontal and vertical separation being 3.7 nautical miles and 749 feet, as depicted in Figure 34 and Figure 35.

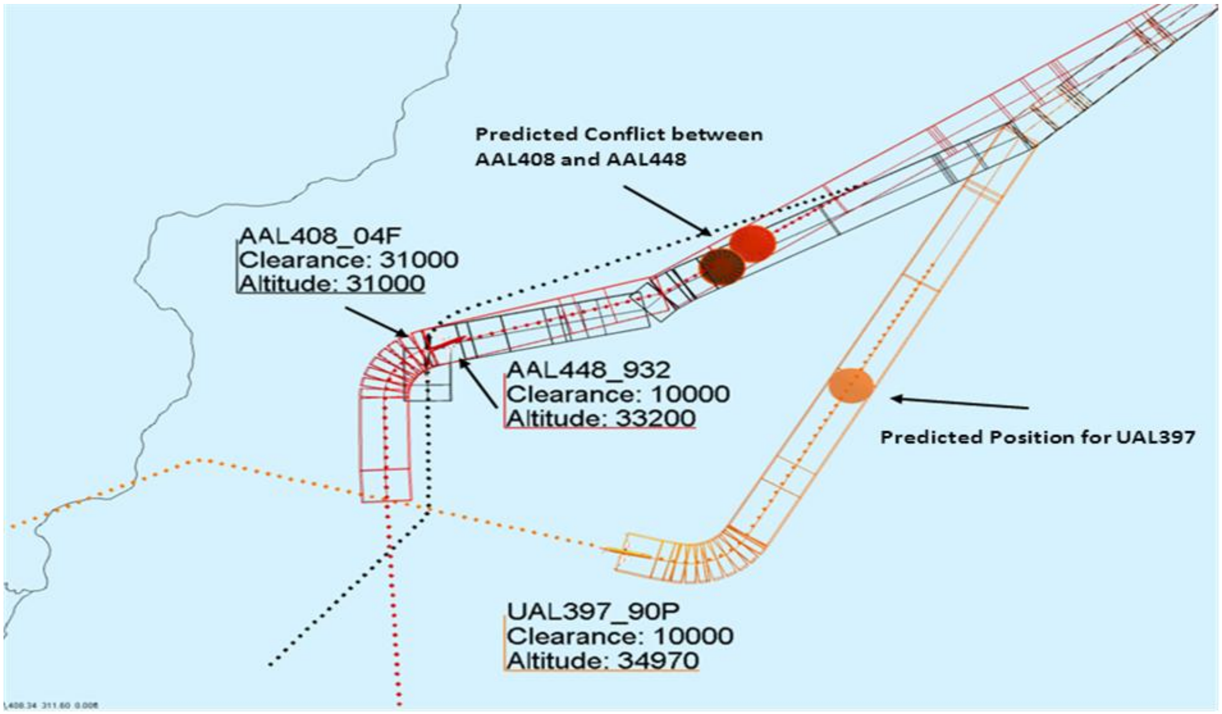

Figure 34: Horizontal Visualization of the Predicted Conflict between AAL408 and AAL448

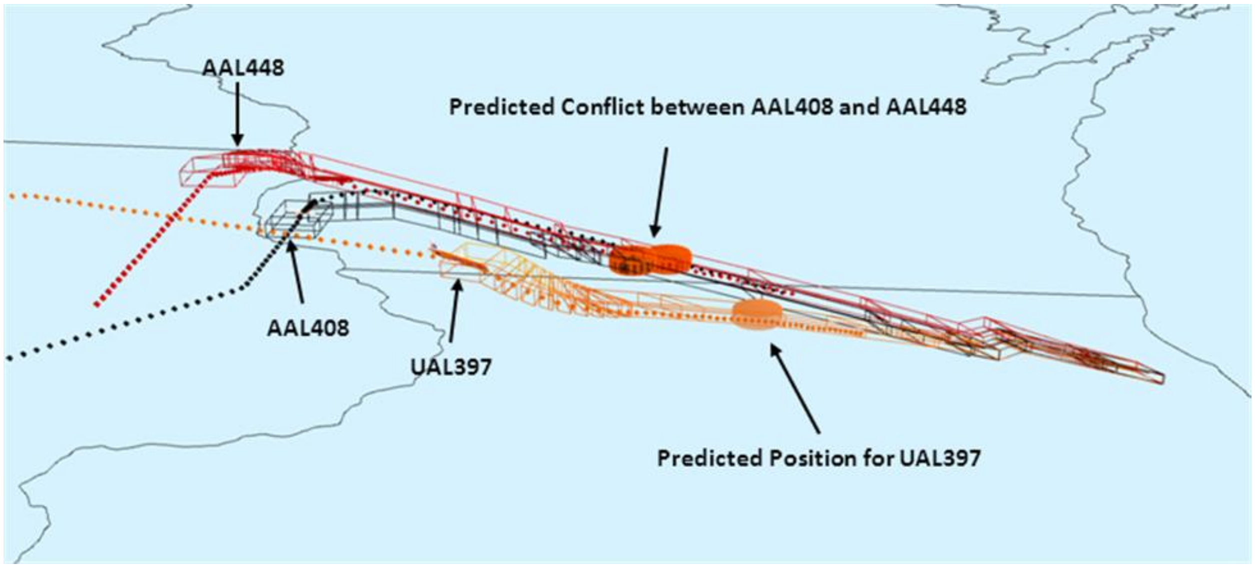

Figure 35: Vertical Visualization of the Predicted Conflict between AAL408 and AAL448

As AAL408 and AAL448 complete the turn and stay on the resolution trajectory, a conflict between the aircraft is missed by the CP, occurring at 81346 seconds with the horizontal and vertical minimum separation being 4.01 nautical miles and 900 feet respectively. In addition, the CP predicts a conflict between AAL408 and UAL397 to occur at 81546 seconds with the horizontal and vertical minimum separation being 1.741 nautical miles and 460 feet respectively. The missed and false alerts are depicted in Figure 36 and Figure 37.

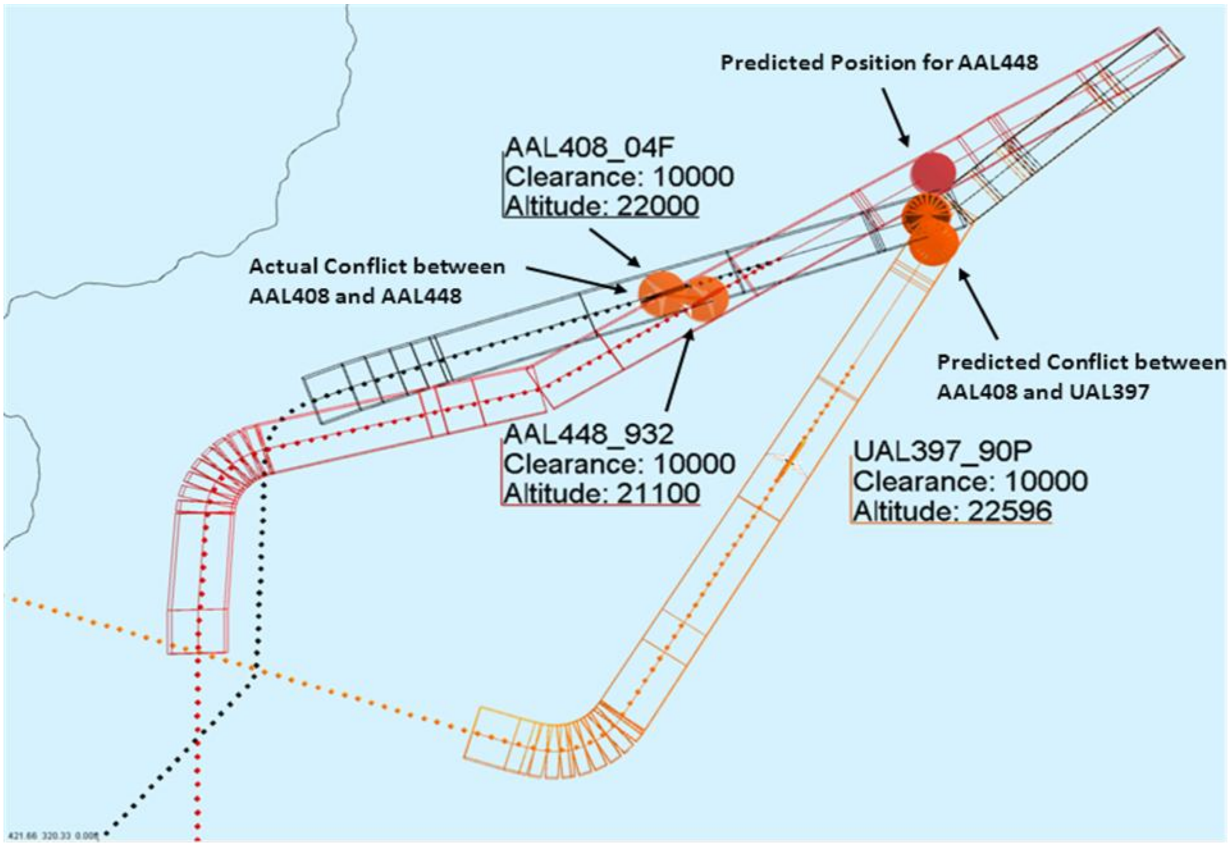

Figure 36: Horizontal Visualization of the False and Missed Alerts

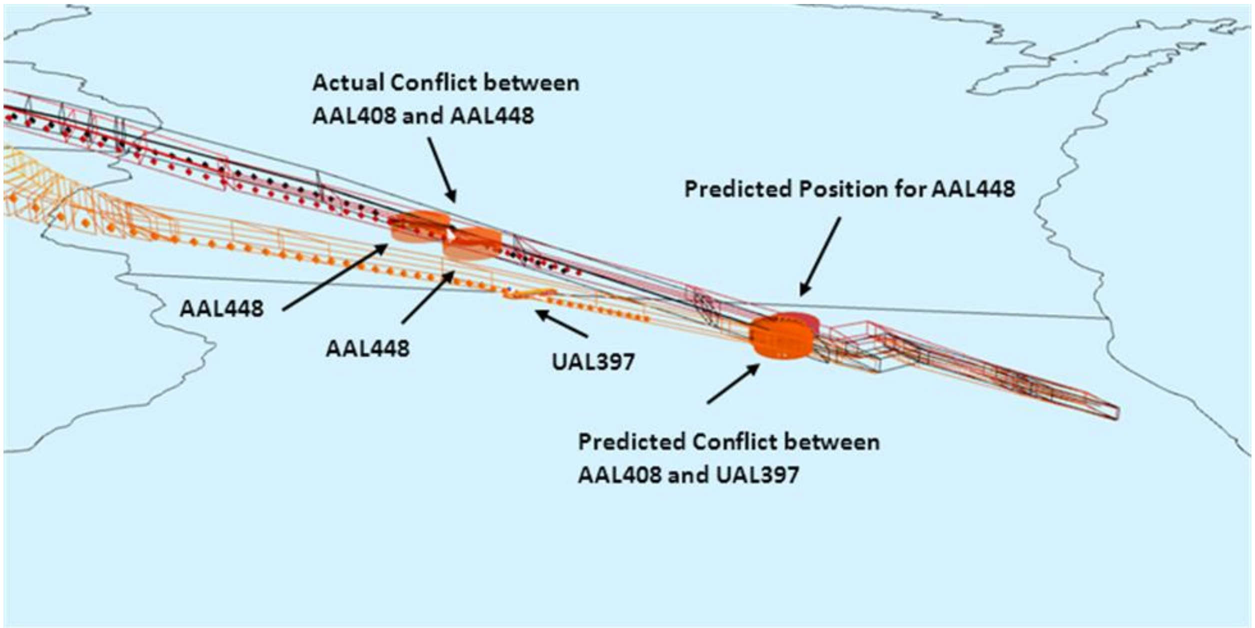

Figure 37: Vertical Visualization of the False and Missed Alerts

Figure 38 illustrates that, in the full intent scenario, aircraft UAL397 conforms to its planned route, AAL448 performs the resolution maneuver with intent entry, and AAL408 does not respond to the aforementioned false alert. Because of the intent consistency, the trajectories generated by the TP conform to the track data and the trajectories are conflict free. As a result, there is no false alert or conflict missed by the CP, as depicted in Figure 39 and Figure 40.

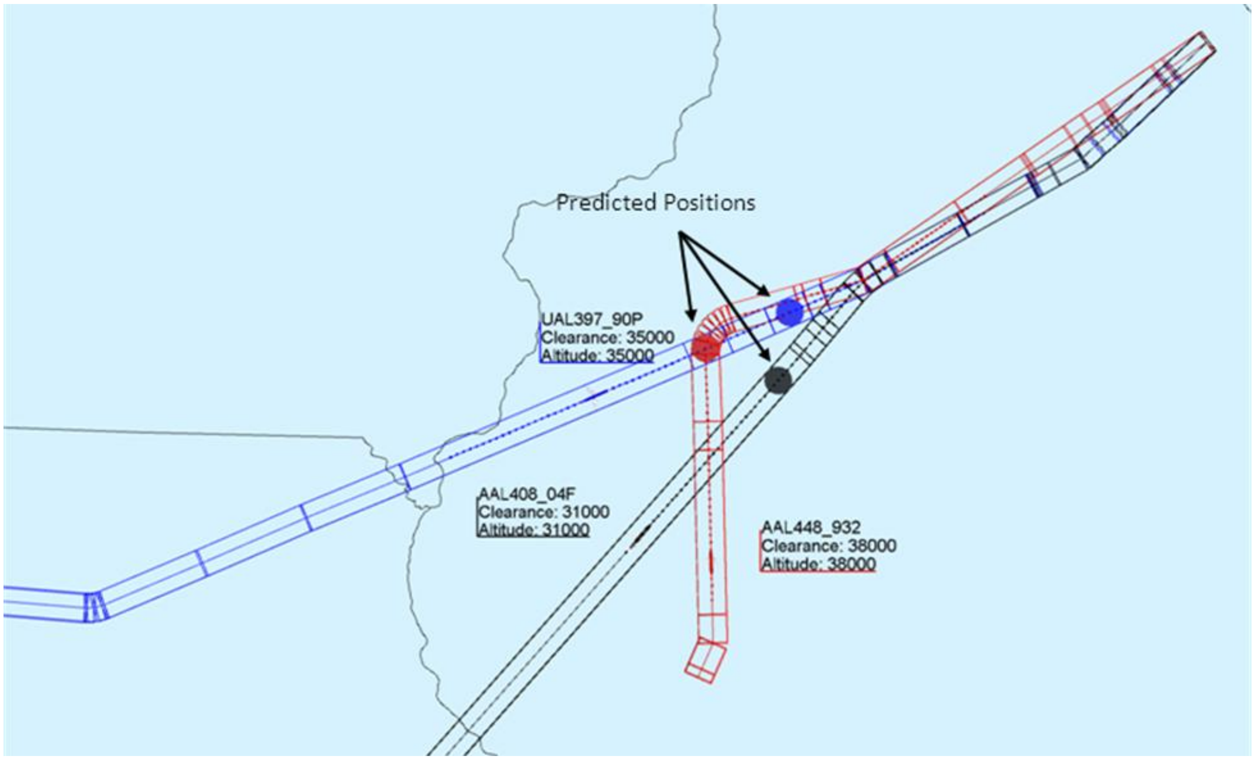

Figure 38: Conforming and Conflict Free Trajectories

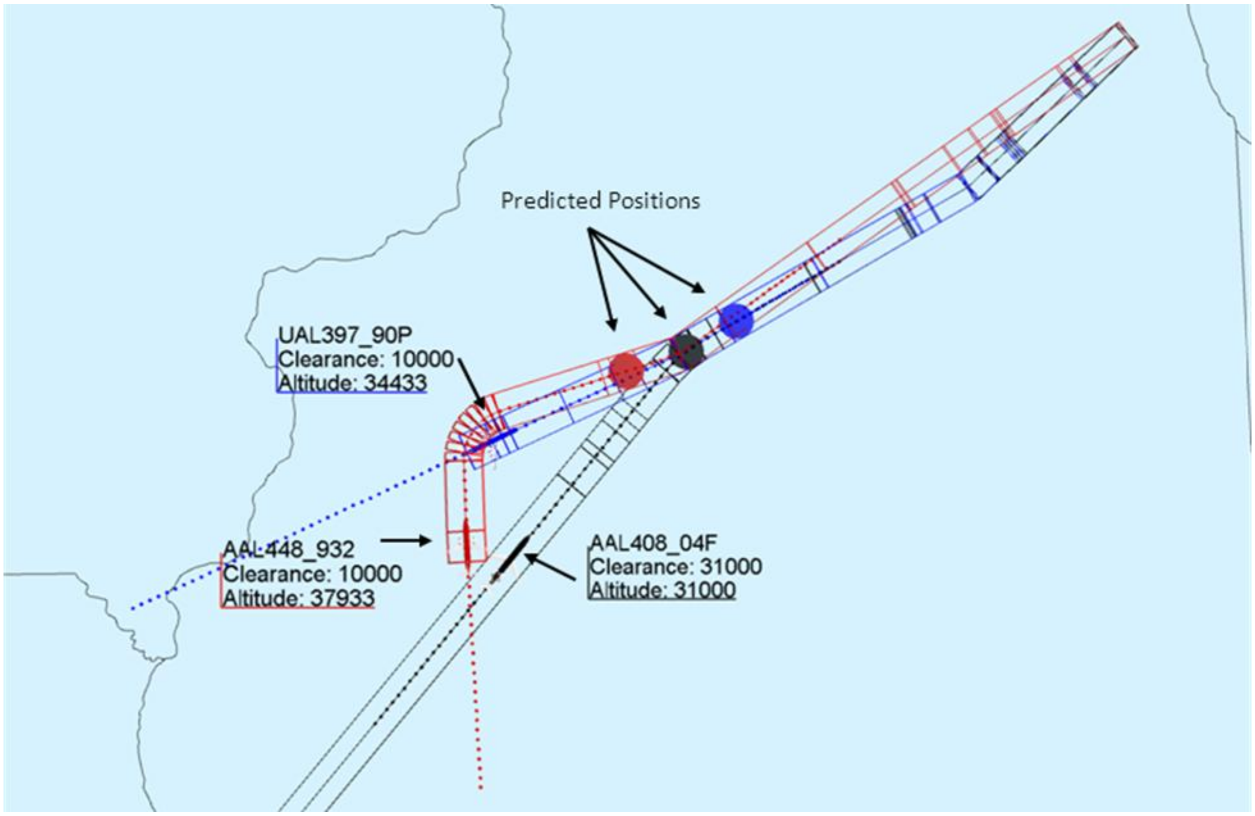

Figure 39: Horizontal Visualization of the Conflict Free Trajectories

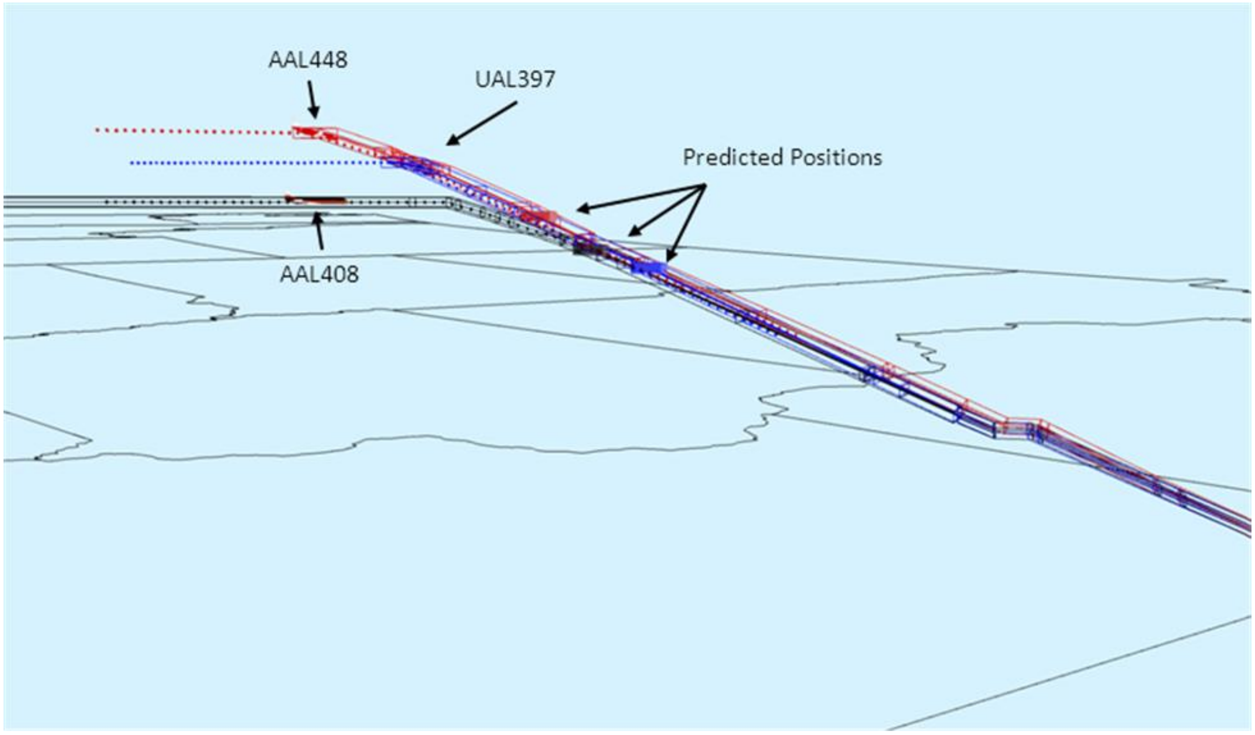

Figure 40: Vertical Visualization of the Conflict Free Trajectories

All three flights -UAL397, AAL408, and AAL448- implement 2-leg maneuvers that are not entered into the ground automation system in the low-intent scenario. As a result, the modeled trajectories are incorrect. The lack of intent information causes two false conflicts, an unnecessary maneuver, and a missed alert. In contrast, when the full clearances are entered into the ground automation the trajectories are modeled correctly and these undesirable events are avoided.

4. Conclusions

CRA is envisioned as an advanced decision support tool for air traffic control deployed within the NextGen TBO initiatives. It predicts future conflicts between aircraft and proposes ranked resolution options, supporting increased use of "closed-loop" clearances by facilitating the entry of controller-selected resolutions. Contrasted with the methods used in today's operations, where amendments are typically issued via voice and are often unknown to the ground automation system, this improved entry of amendments expands the information available to the automation regarding future intent. It is hypothesized that this additional information will increase the accuracy of ground-based trajectory modeling and improve conflict probe alert performance.

The objective of this study, as defined in Section 1.3, is to investigate the benefits of improved trajectory modeling and conflict probe performance due to increased entry of controller intent, using a fast-time simulation methodology that involves a CRA prototype and ERAM-like system. The assumption that CRA will increase intent information available to ground automation systems will be validated in separate analysis. This is one of a series of studies to estimate a number of potential benefits of CRA; see Section 1.3 for a full listing. This study utilized a sound methodology utilizing several powerful tools and platforms including fast-time simulation airspace and ATC software, both internally developed and commercial off-the-shelf statistical and graphical platforms, and advanced multi-regression modeling to synthesize the results and estimate the net effects. Almost 45,000 flights over 240 hours are simulated.

Overall, a performance improvement is observed in both trajectory modeling and conflict probe alerts with increasing levels of intent entry. The model fits the output data closely, capturing between 97 and 100% of the variation in the data for different response variables, and indicates a strong non-linear effect from the intent level parameter- the size of the effect is highest at lower levels of intent entry. The results indicate a potential improvement in trajectory modeling: 61% decrease in the overall average horizontal error and 42% decrease in the overall average vertical error when comparing scenarios that simulated the least amount of controller intent entry to scenarios with complete entry of full clearances. In addition, the number of trajectories generated that do not coincide with a flight plan amendment decrease by 42% overall between these scenarios, indicating that the trajectories generated are more stable and that less reconformance rebuilds are necessary with more complete entry of a controller's future intent.

These improvements in trajectory prediction and more accurate trajectories lead to better performance of the conflict probe. Two metrics that are used to demonstrate conflict alert performance are the first quartile of predicted warning time, and the count of alerts with duration greater than one minute. From the statistical model, there is an overall increase of 58 seconds in the first quartile of predicted warning time of alerts when increasing full entry of 2-part clearances to the ground automation from 0 to 100%. The count of alerts with duration greater than one minute reflects how often alerts are not removed upon issuing an amendment, and these alerts decrease by an average of 80% over all experimental runs when increasing full entry of 2-part clearances from 0 through 100%.

In summary, this study presents a comprehensive simulation of improved intent entry and evaluates the impact that Conflict Resolution Advisories could have on the performance of the ground automation with respect to trajectory modeling and conflict alert generation. The authors employed metrics that reflect important performance aspects of trajectory modeling and conflict probe alerting. The results indicate a significant impact and definite trend of performance improvement with increasing entry of full 2-part clearances, which CRA facilitates.

5. Glossary

ANG-C41	FAA's Concept Analysis Branch
ANSP	Air Navigation Service Provider
ARTCC	Air Route Traffic Control Center
AJG	FAA's Joint Planning Group
ATC	Air Traffic Control
ATO-P	Air Traffic Organization – NextGen and Operations Planning Office
CONUS	Continental United States
CP	Conflict Probe
CRA	Conflict Resolutions Advisories
Datacomm	Data communications
DOE	Design of Experiment
DOF	Direction of Flight
DST	Decision Support Tool
ETMS	Enhanced Traffic Management System
FAA	Federal Aviation Administration
FB	Fuel Burn
FD	Flight Delay
FDS	Flight Data Set
FT	Flight Time
FY	Fiscal Year
IFR	Instrument Flight Rules
JEDI	Java En Route Development Initiative
JPDO	Joint Planning Development Office
MySQL	The MySQL® open source relational database system
NAS	National Airspace System
NASA	National Aeronautics and Space Administration
NextGen	Next Generation Air Transportation System
OPSNET	Operations Network
PARR	Problem Analysis Resolution and Ranking
PLA	Project Level Agreement
TBO	Trajectory-Based Operations
TP	Trajectory Predictor
UTC	Coordinated Universal Time
VFR	Visual Flight Rules
VHF	Very High Frequency
ZAU	Chicago ARTCC
ZDV	Denver ARTCC
ZLA	Los Angles ARTCC
ZMA	Miami ARTCC
ZNY	New York ARTCC

6. References

1. Box, G., Hunter, J. S., and Hunter, W. G., *Statistics for Experimenters, Design, Innovation, and Discovery, Second Edition,* Hoboken, NJ, John Wiley & Sons, 2005.

2. Crowell, A. T., Fabian, A. J., Nelson, N. A., *An Interactive 4D Visualization System for Air Traffic Concept Analysis*, 31st Digital Avionics Systems Conference, October 15-18, 2012.

3. Crowell, A. T., Fabian, A. J., Young, C. M., Musialek, B., Paglione, M. M., *Evaluation of Parameter Adjustments to the En Route Automation Modernization's Conflict Probe*, FAA Technical Note, DOT/FAA/TC-TN12/2, 2011.

4. Federal Aviation Administration, *Concept of Operations for the Next Generation Air Transportation System, Version 2.0*, Joint Planning and Development Office, 1500 K Street, Suite 500, Washington, DC 20005, June 13, 2007.

5. Federal Aviation Administration, *Next Generation Air Transportation System Integrated Plan*, Joint Planning and Development Office, 1500 K Street, Suite 500, Washington, DC 20005, December 12, 2004.

6. Federal Aviation Administration, *NextGen Project Level Agreement: TBO - Conflict Resolutions Advisories - Voice and Datacomm*, Research and Technology Development Office, NextGen and Operations Planning AJP-6, March 16, 2010.

7. Federal Aviation Administration, *TBO - Conflict Resolutions Advisories Benefits Plan, Version 0.1*, ATO-P, FAA Simulation and Analysis Group, William J. Hughes Technical Center, October 1, 2010.

8. Groupy, J., and Creighton, L., *Introduction to Design of Experiments with JMP® Examples, Third Edition*, Cary, NC, SAS Press Series, 2007.

9. Hicks, C. R., *Fundamental Concepts in the Design of Experiments, Fourth Edition*, New York, NY, Saunders College Publishing, 1993.

10. Kirk, D.B., Arthur, W., Malik, Z., Meyer, K., and Steinbach, D., *Initial Trajectory Information Exchange Analysis* (Draft), The MITRE Corporation, McLean, VA, July 2012.

11. Kirk, D. B., Meyer, K. A., Mills, S. H., and Rozen, N. E., *Benefit Mechanisms and Assessment Methodology for Initial Conflict Resolution Advisories*, MTR110317, The MITRE Corporation, McLean, VA, 2011a.

12. Kirk, D.B., Rozen, N.E., Waters, T., Arthur, W., and Meyer, K.A., *Problem Detection & Resolution Functional Performance Assessment – Plan and Interim Analysis Results, Revision 4*, MTR110414, The MITRE Corporation, McLean, VA, 2011b.

13. Kuo, V. and Idris, H., *Safety Benefit Mechanisms for Improved Intent Using Initial Conflict Resolution Advisories*, FAA Task Order CA1513, Engility Corporation, Billerica, MA, June 2012.

14. Montgomery, D. C., *Design and Analysis of Experiments, Fourth Edition*, New York, NY, John Wiley & Sons, 1997.

15. Paglione, M. M., Oaks, R. D., *Implementation and Metrics for a Trajectory Prediction Validation Methodology*, American Institute of Aeronautics and Astronautics (AIAA) Guidance, Navigation, and Control Conference, Hilton Head, S.C., August 2007.

16. Paglione, M. M., Oaks, R. D., and Bilimoria, K. D., *Methodology for Generating Conflict Scenarios by Time Shifting Recorded Traffic Data*, AIAA 2003-6724, American Institute of Aeronautics and Astronautics (AIAA) Aviation Technology, Integration, and Operations Conference, November 17-19, 2003.

17. SAS Institute Inc., *JMP® Software: Classic Design of Experiments*, [Course Notes], Cary, NC, 2007.

18. SAS Institute Inc., *Safeguarding the Skies*, http://www.jmp.com/software/success/faa.shtml, [cited: February 28, 2011].

19. Young, C. M., *Project Plan for CRA Fast-Time Simulation Study II Investigating Benefit from Improved Intent Entry*, FAA Memorandum, January 3, 2012.

Appendix A

This appendix provides paired *t*-test results for comparing trajectory counts at different intent levels as described in Section 3.1.1. The two metrics are the count of all trajectories and the count of trajectories that are not matched to a clearance. Each is presented as an average count per flight in Table 13, which provides the difference in means and Student's paired *t*-statistic for each comparison of a reduced intent scenario to the full intent scenario. Positive differences in the table reflect an increase from the full intent scenario to the reduced intent scenario.

Table 13: Paired *t*-test Results for Trajectory Counts in All Scenarios

			Mean Difference		Paired *t*-Statistic	
ARTCC	**Year**	**Intent**	**Total Trajectory Count**	**Traj. Not Matched to Clearance**	**Total Trajectory Count**	**Traj. Not Matched to Clearance**
ZAU	2018	HI	0.2	0.2	10.0	9.4
		MD	0.4	0.4	16.4	15.7
		LO	0.7	0.6	20.6	20.2
		NN	1.0	0.8	25.1	24.6
	2025	HI	0.2	0.2	11.9	11.9
		MD	0.4	0.4	17.9	17.9
		LO	0.8	0.6	22.9	22.2
		NN	1.1	0.9	28.0	27.4
ZDV	2018	HI	0.2	0.2	8.5	8.0
		MD	0.3	0.3	11.7	11.5
		LO	0.5	0.4	15.9	15.7
		NN	0.7	0.6	18.0	17.3
	2025	HI	0.2	0.2	7.4	7.2
		MD	0.4	0.3	11.0	10.5
		LO	0.5	0.5	16.3	16.1
		NN	0.7	0.7	16.1	15.4
ZLA	2018	HI	0.2	0.2	10.7	10.9
		MD	0.5	0.5	14.7	14.7
		LO	0.8	0.6	17.5	17.0
		NN	1.1	0.9	23.5	23.1
	2025	HI	0.4	0.3	10.7	9.9
		MD	0.6	0.5	15.2	14.5
		LO	1.0	0.8	14.0	12.9
		NN	1.3	1.1	24.9	23.9

			Mean Difference		Paired *t*-Statistic	
ARTCC	**Year**	**Intent**	**Total Trajectory Count**	**Traj. Not Matched to Clearance**	**Total Trajectory Count**	**Traj. Not Matched to Clearance**
ZMA	2018	HI	0.2	0.1	9.2	8.9
		MD	0.4	0.3	14.0	13.9
		LO	0.6	0.5	18.0	17.7
		NN	0.8	0.7	22.8	23.5
	2025	HI	0.2	0.2	9.4	9.1
		MD	0.4	0.4	14.8	14.2
		LO	0.7	0.6	19.4	18.9
		NN	1.0	0.8	24.4	24.0
ZNY	2018	HI	0.3	0.2	4.2	3.8
		MD	0.4	0.3	16.6	16.2
		LO	0.7	0.6	10.9	9.5
		NN	0.9	0.7	25.4	25.1
	2025	HI	0.2	0.2	13.2	12.5
		MD	0.4	0.4	18.6	17.8
		LO	0.7	0.6	23.6	22.8
		NN	1.0	0.8	28.2	28.0

Appendix B

This appendix provides paired *t*-test results for four types of trajectory errors: Average Absolute Cross Track Error, Average Absolute Along Track Error, Average Absolute Vertical Error, and Average Horizontal Error, as described in Section 3.1.2. Table 14 contains the difference in means and Student's paired *t*-statistic for each comparison. Positive differences in the table reflect an increase from the full intent scenario to the reduced intent scenario.

Table 14: Paired *t*-test Results for Trajectory Errors in All Scenarios

			Mean Difference				Paired *t*-Statistic			
ARTCC	**Year**	**Intent**	**Avg AACTE (NM)**	**Avg AAATE (NM)**	**Avg AAVE (ft)**	**Avg AHE (NM)**	**Avg AACTE**	**Avg AAATE**	**Avg AAVE**	**Avg AHE**
ZAU	2018	HI	0.031	0.026	10.100	0.051	6.8	3.8	4.7	6.0
		MD	0.076	0.060	23.678	0.118	9.8	8.7	8.8	11.0
		LO	0.126	0.094	39.285	0.189	11.2	10.5	10.9	12.8
		NN	0.177	0.102	56.118	0.234	13.5	12.8	12.4	14.7
	2025	HI	0.033	0.036	12.693	0.059	8.0	6.6	6.0	8.9
		MD	0.084	0.063	28.832	0.125	9.1	9.6	8.5	10.8
		LO	0.132	0.109	44.717	0.203	11.8	11.0	11.5	13.5
		NN	0.199	0.119	59.805	0.263	14.7	13.5	13.5	16.0
ZDV	2018	HI	0.024	0.020	3.505	0.040	5.7	5.2	3.7	6.7
		MD	0.054	0.031	5.416	0.074	7.0	7.9	4.5	8.3
		LO	0.091	0.050	9.759	0.121	8.7	9.4	5.9	10.0
		NN	0.111	0.052	14.202	0.140	10.3	11.1	6.9	11.5
	2025	HI	0.037	0.029	3.857	0.056	6.4	4.3	4.5	6.4
		MD	0.055	0.036	6.482	0.078	8.8	6.6	6.2	9.3
		LO	0.085	0.046	13.120	0.114	10.8	10.9	7.2	12.1
		NN	0.115	0.061	16.790	0.149	11.9	8.8	6.9	12.5

			Mean Difference				Paired *t*-Statistic			
ARTCC	**Year**	**Intent**	**Avg AACTE (NM)**	**Avg AAATE (NM)**	**Avg AAVE (ft)**	**Avg AHE (NM)**	**Avg AACTE**	**Avg AAATE**	**Avg AAVE**	**Avg AHE**
ZLA	2018	HI	0.026	0.035	8.753	0.047	6.9	3.2	4.4	6.4
		MD	0.079	0.074	19.865	0.129	9.0	7.2	7.9	10.2
		LO	0.130	0.106	26.120	0.185	10.7	5.5	8.0	11.0
		NN	0.200	0.148	44.582	0.269	13.6	7.2	10.6	14.0
	2025	HI	0.052	0.049	14.126	0.089	7.5	6.4	5.3	7.4
		MD	0.132	0.102	22.070	0.198	3.6	5.8	9.1	4.5
		LO	0.188	0.138	39.860	0.275	5.0	7.8	10.5	6.0
		NN	0.284	0.203	60.734	0.396	7.2	8.6	12.2	8.0
ZMA	2018	HI	0.017	0.027	11.989	0.035	5.7	4.0	5.6	5.6
		MD	0.049	0.050	29.140	0.086	8.1	7.5	7.7	9.4
		LO	0.075	0.071	42.448	0.123	9.4	7.6	9.5	10.4
		NN	0.104	0.076	58.016	0.150	11.9	10.8	11.4	13.8
	2025	HI	0.032	0.024	12.722	0.048	6.3	4.8	4.7	6.7
		MD	0.050	0.044	29.973	0.083	9.1	7.5	8.0	10.4
		LO	0.090	0.062	47.029	0.130	11.9	9.3	10.1	12.6
		NN	0.143	0.087	67.374	0.192	14.3	13.1	12.0	15.6
ZNY	2018	HI	0.036	0.045	13.593	0.066	5.2	4.1	5.2	6.1
		MD	0.053	0.075	19.649	0.104	6.4	6.2	9.2	8.6
		LO	0.098	0.093	39.225	0.159	9.0	7.2	10.3	10.6
		NN	0.133	0.114	47.820	0.200	11.4	7.8	12.5	12.4
	2025	HI	0.022	0.048	15.008	0.057	5.2	4.6	6.0	6.3
		MD	0.058	0.062	19.572	0.096	8.4	5.8	6.4	8.9
		LO	0.100	0.115	37.302	0.174	10.5	7.5	10.0	11.3
		NN	0.136	0.134	51.380	0.214	12.0	8.2	12.0	12.9

Appendix C

This appendix provides additional graphs depicting trajectory error as a function of look ahead time as described in Section 3.1.2. Figure 41 and Figure 42 are set up in a similar fashion to Figure 7.

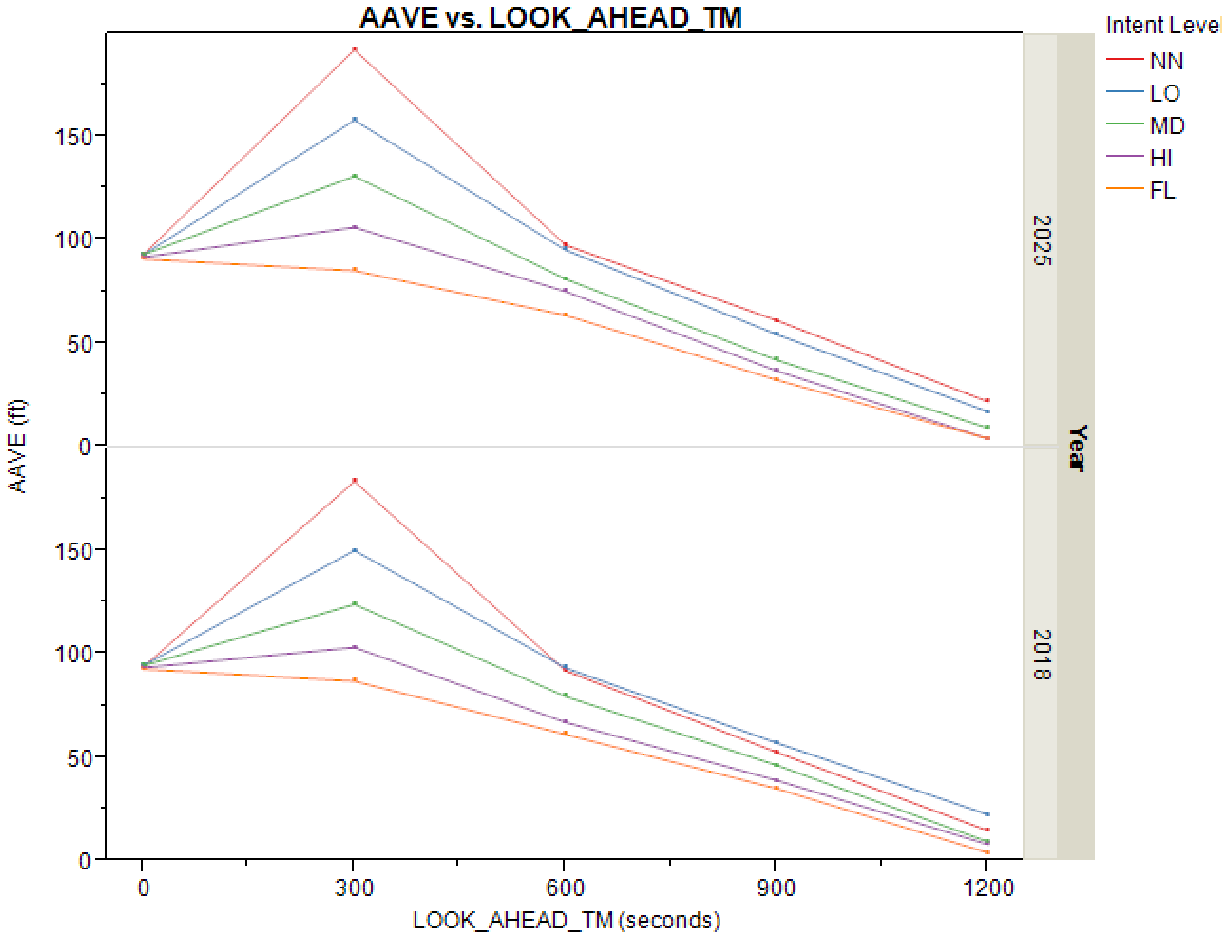

Figure 41: Vertical Trajectory Error vs. Look Ahead Time

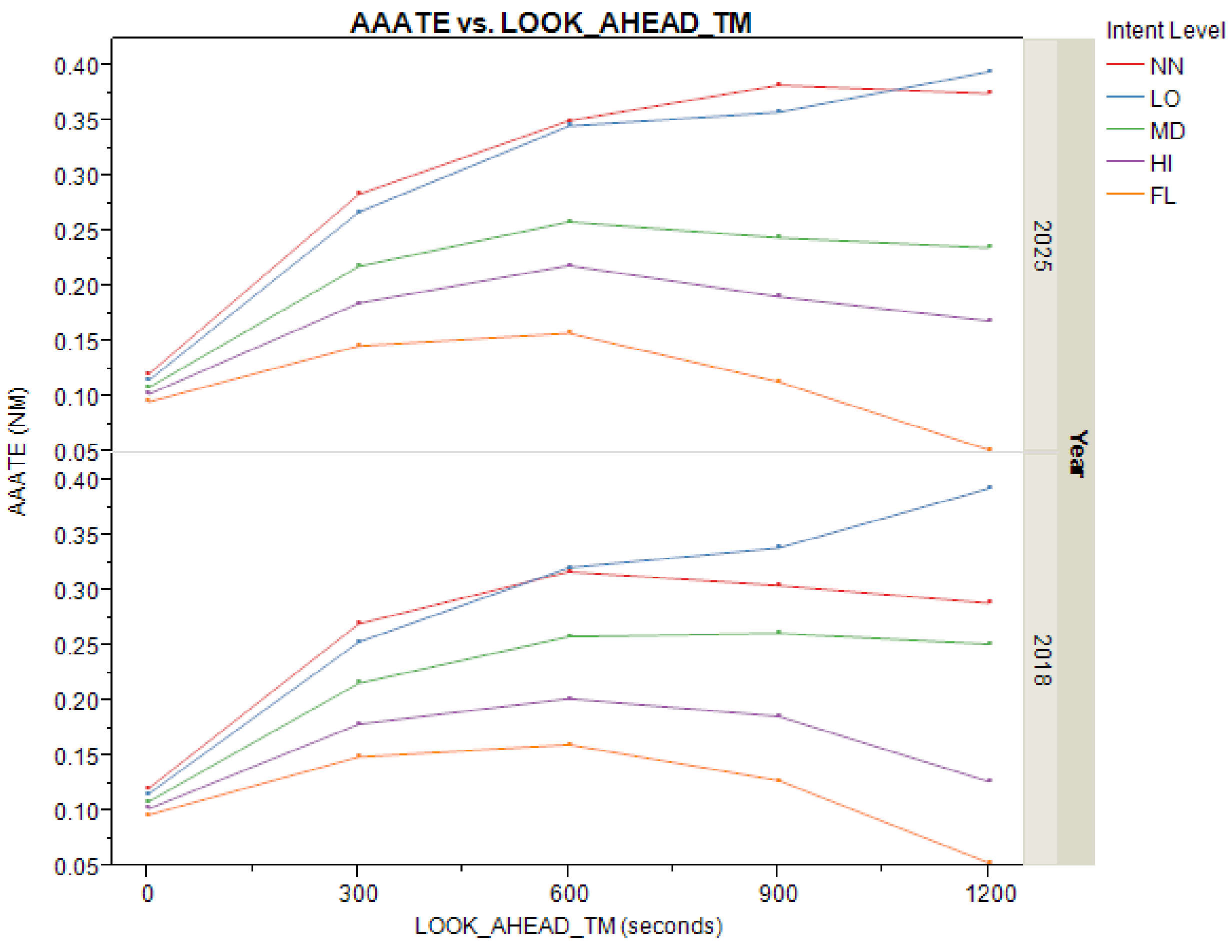

Figure 42: Along Track Trajectory Error vs. Look Ahead Time

Appendix D

This appendix provides additional graphs with histograms of alert duration as a function of look ahead time as described in Section 3.2. Figure 43- Figure 51 are set up in a similar fashion to Figure 9.

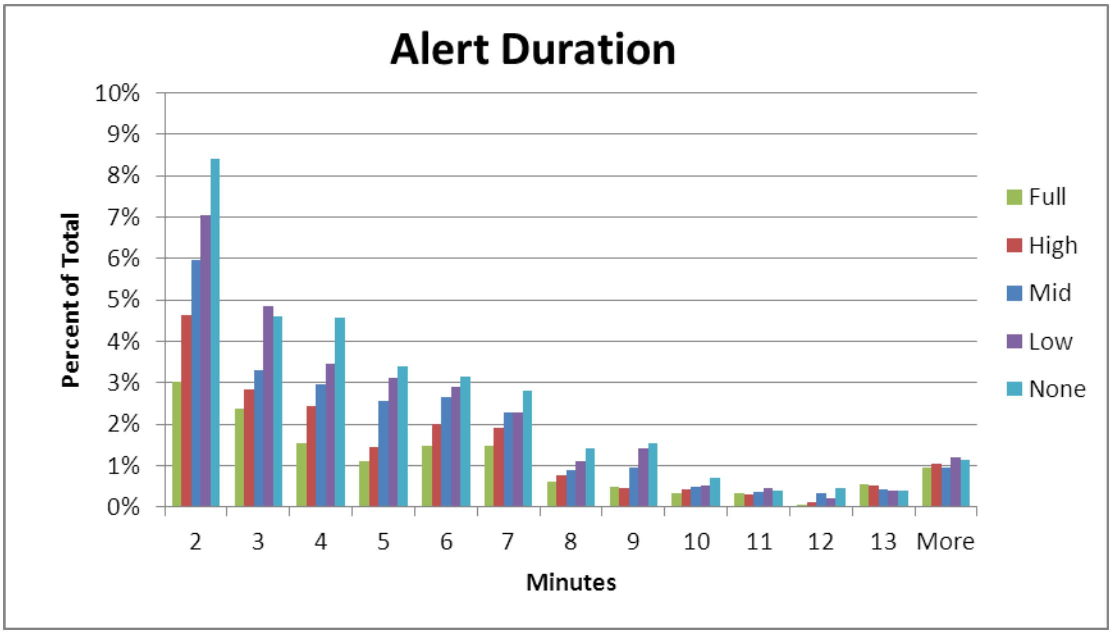

Figure 43: Percent of Alerts with Duration Exceeding One Minute for ZAU 2025

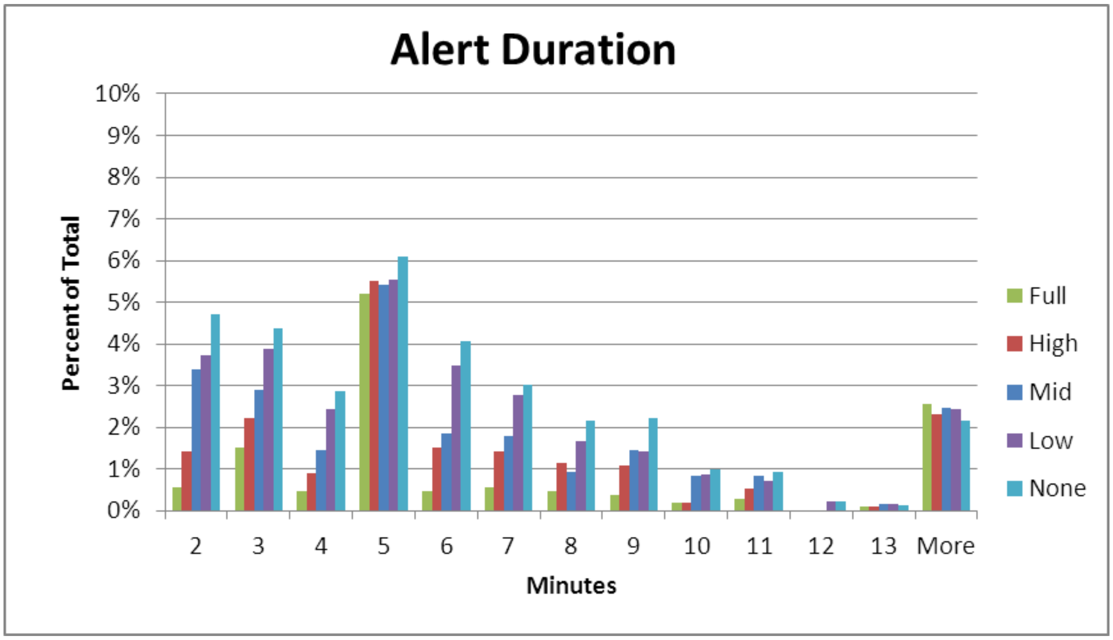

Figure 44: Percent of Alerts with Duration Exceeding One Minute for ZDV 2018

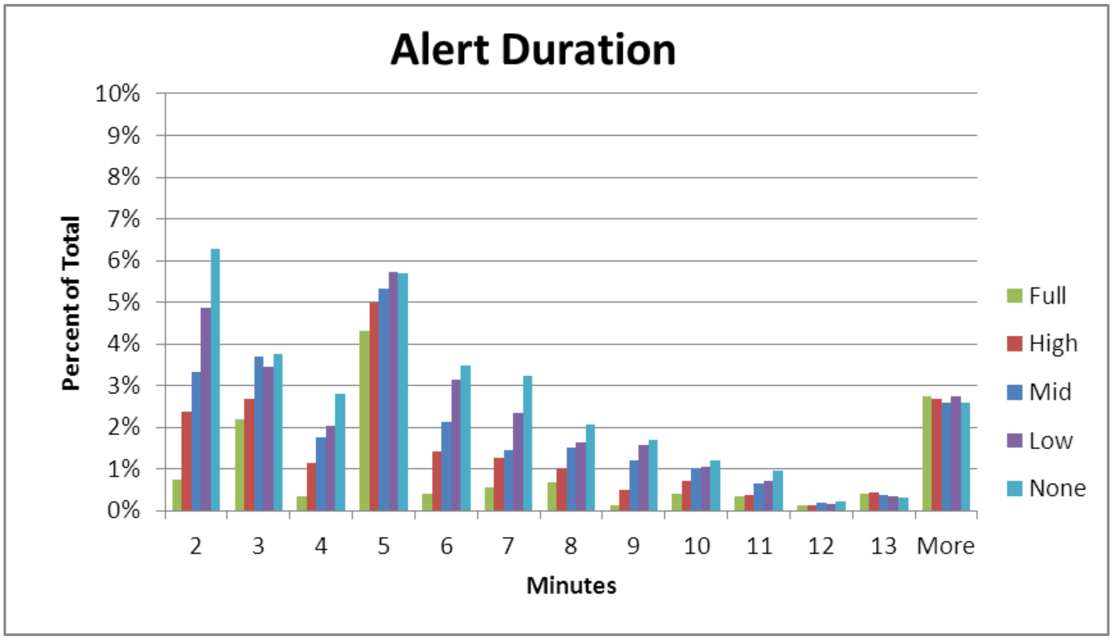

Figure 45: Percent of Alerts with Duration Exceeding One Minute for ZDV 2025

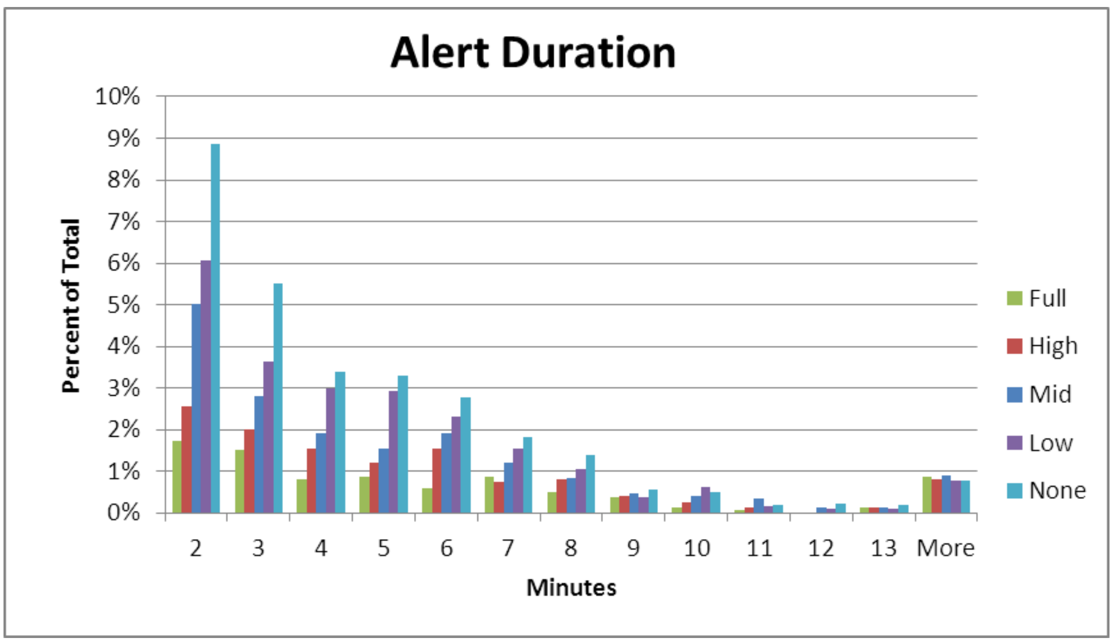

Figure 46: Percent of Alerts with Duration Exceeding One Minute for ZLA 2018

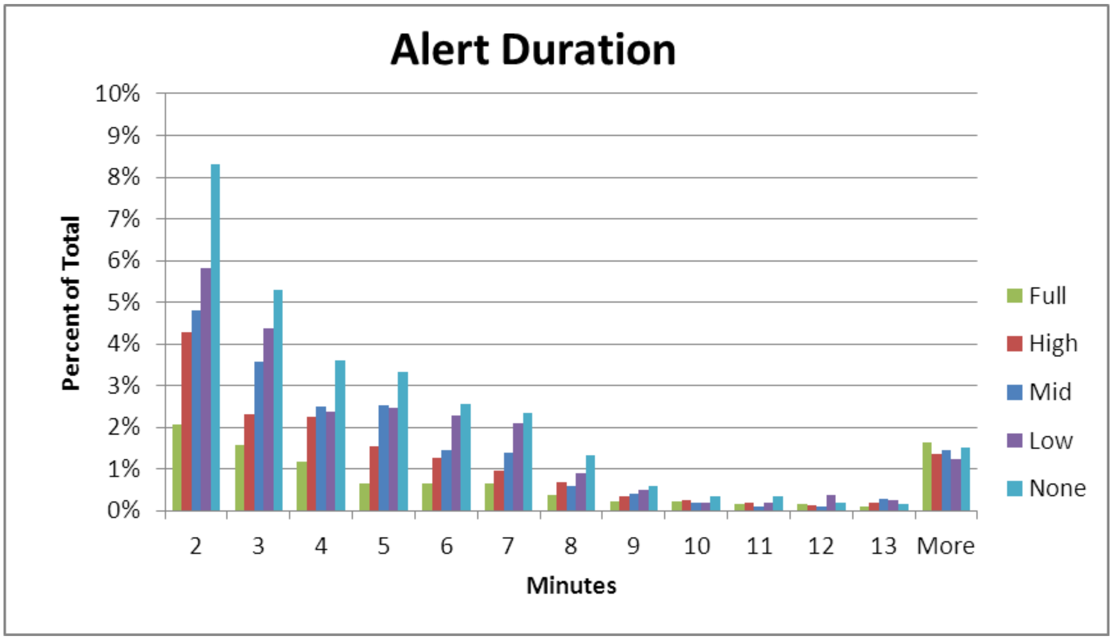

Figure 47: Percent of Alerts with Duration Exceeding One Minute for ZLA 2025

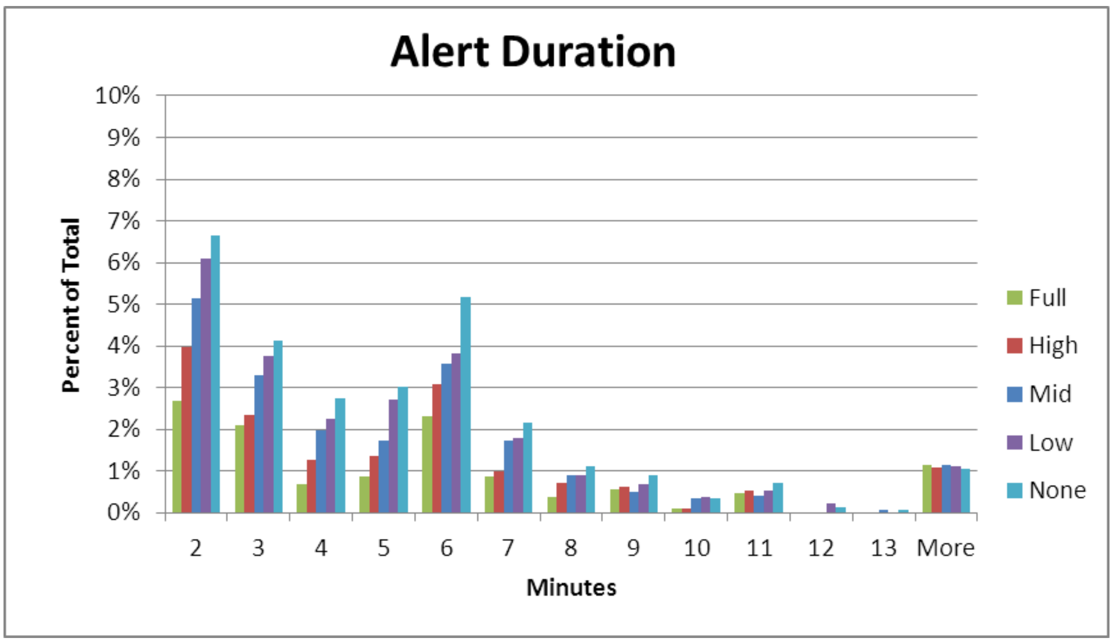

Figure 48: Percent of Alerts with Duration Exceeding One Minute for ZMA 2018

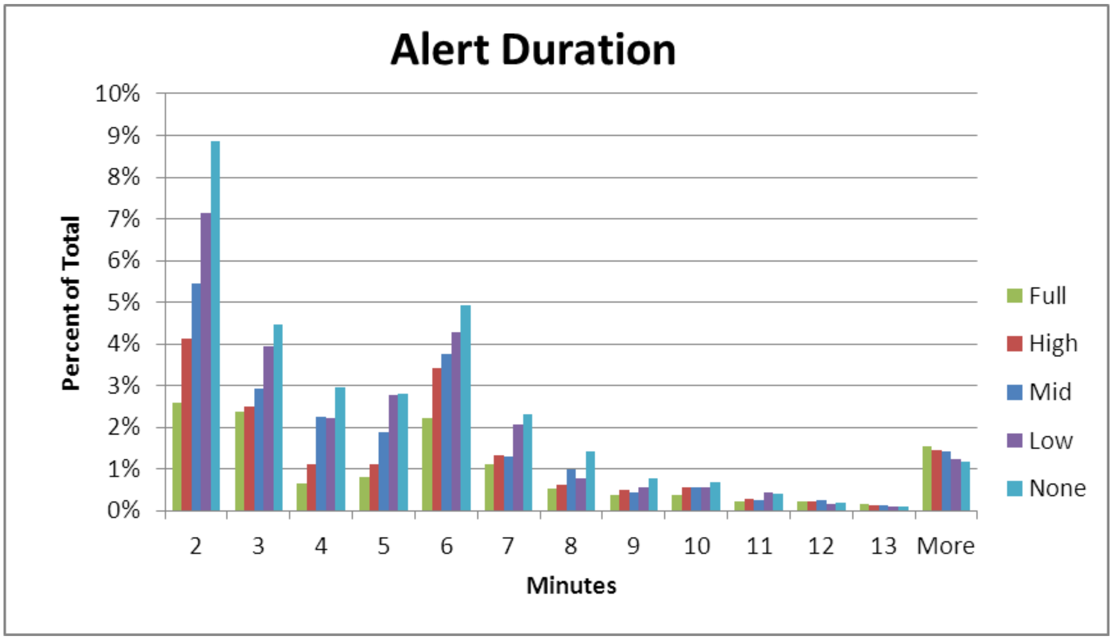

Figure 49: Percent of Alerts with Duration Exceeding One Minute for ZMA 2025

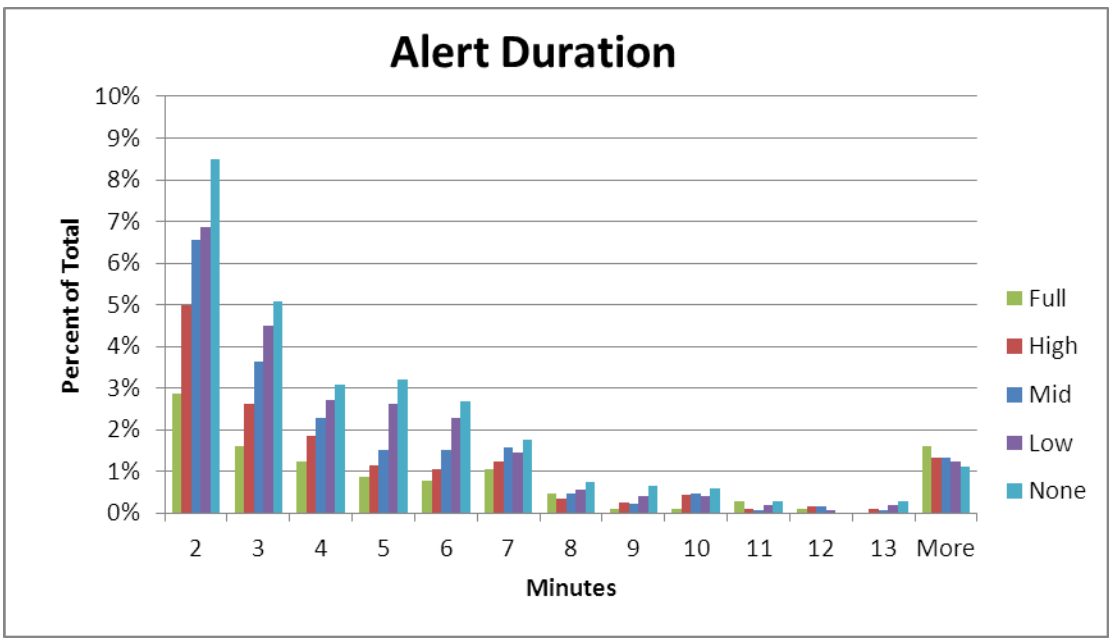

Figure 50: Percent of Alerts with Duration Exceeding One Minute for ZNY 2018

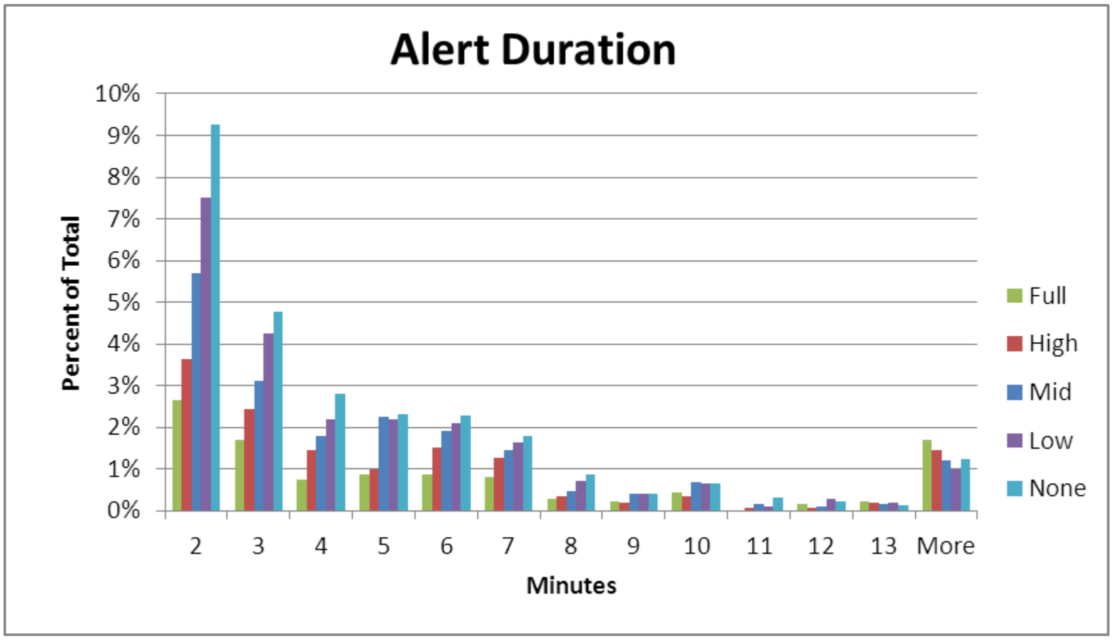

Figure 51: Percent of Alerts with Duration Exceeding One Minute for ZNY 2025

Appendix E

This appendix provides additional tables with conflict alert statistics for the various scenarios as described in Section 3.2. Table 15 - Table 18 contain similar information as Table 6.

Table 15: Alert Statistics for ZDV Scenarios

Intent Level	Year	N	Q1 of Predicted Warning Time (seconds)	% Alerts w/ Duration > 1 min.
FL	2018	1059	320	12.7
	2025	1456	321	13.5
HI	2018	1122	310	18.4
	2025	1560	313	19.8
MD	2018	1179	303	23.5
	2025	1652	298	25.2
LO	2018	1829	295	20.3
	2025	1710	290	29.8
NN	2018	1397	280	33.9
	2025	1892	282	34.3

Table 16: Alert Statistics for ZLA Scenarios

Intent Level	Year	N	Q1 of Predicted Warning Time (seconds)	% Alerts w/ Duration > 1 min.
FL	2018	1376	297	8.5
	2025	1848	298	9.6
HI	2018	1489	291	12.2
	2025	2073	287	15.8
MD	2018	1676	282	17.6
	2025	2210	281	19.3
LO	2018	1810	275	22.7
	2025	2446	270	23.0
NN	2018	2158	241	29.5
	2025	2978	222	29.9

Table 17: Alert Statistics for ZMA Scenarios

Intent Level	Year	N	Q1 of Predicted Warning Time (seconds)	% Alerts w/ Duration > 1 min.
FL	2018	1043	288	12.2
	2025	1346	287	13.2
HI	2018	1107	280	16.1
	2025	1434	282	17.4
MD	2018	1208	275	20.9
	2025	1601	273	21.6
LO	2018	1332	268	24.2
	2025	1794	263	26.3
NN	2018	1429	261	28.2
	2025	2032	242	31.1

Table 18: Alert Statistics for ZNY Scenarios

Intent Level	Year	N	Q1 of Predicted Warning Time (seconds)	% Alerts w/ Duration > 1 min.
FL	2018	1051	293	11.0
	2025	1360	293	10.7
HI	2018	1140	283	15.6
	2025	1511	284	14.0
MD	2018	1267	269	19.9
	2025	1736	269	19.4
LO	2018	1445	246	23.5
	2025	2001	247	23.2
NN	2018	1717	208	28.0
	2025	2281	209	27.0