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A METHODOLOGY FOR AUTOMATED TRAJECTORY PREDICTION ANALYSIS

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A number of air traffic management decision support tools (DST) are being developed to help air traffic managers and controllers improve capacity, efficiency, and safety in the National Airspace System. Although DST functionality may vary widely, trajectory prediction algorithms can be found at the core of most DST. A methodology is presented for the automated statistical analysis of trajectory prediction accuracy as a function of phase of flight (level-flight, climb, descent) and look-ahead time. The methodology is focused on improving trajectory prediction algorithm performance for DST applications such as conflict detection and arrival metering. The methodology has been implemented in software and tested with air traffic data. Aggregate trajectory prediction accuracy statistics are computed and displayed in histogram format based on 2,774 large commercial jet flights from five different days of Fort Worth Center air traffic data. The results show that trajectory prediction anomalies can be detected by examining error distributions for large numbers of trajectory predictions. The ability of the trajectory analysis methodology to detect the effects of subsequent changes to the trajectory prediction algorithm and to aircraft performance model parameters was also demonstrated.

Nomenclature

$Altitude_p$	=	predicted altitude
$Altitude_t$	=	radar track altitude
Ψ_p	=	predicted course
T_n	=	look-ahead time n
ΔX	=	difference in x-coordinates
ΔY	=	difference in y-coordinates
X_p	=	predicted x-coordinate position
X_t	=	radar track x-coordinate position
Y_p	=	predicted y-coordinate position
Y_t	=	radar track y-coordinate position

Introduction

TRAJECTORY prediction algorithms are a critical core component of decision support tools (DST) for conflict detection, arrival metering, and other applications in air traffic management automation. A 4-dimensional (4D) trajectory prediction contains data specifying the predicted horizontal and vertical position of an aircraft over some time span into the future, or time horizon. The ability of the trajectory prediction algorithm to accurately predict 4D

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trajectories for a wide variety of aircraft types under a number of different flight conditions is likely the single most important factor in determining the overall accuracy and effectiveness of an air traffic management DST.

Trajectory predictions form the basis for the main, application dependent, DST calculations. For example, conflict detection applications compare trajectory predictions of a number of aircraft against one another in order to identify those aircraft pairs that may be in conflict at some time in the future (i.e., horizontal and vertical separation below some specified minimum). Arrival metering applications depend on trajectory predictions to determine the times when aircraft will pass over a specified location, such as a meter fix. In both applications, the accuracy of aircraft trajectory predictions will directly affect DST calculations and, ultimately, the utility of the DST.

The prediction time horizon of interest is also application dependent and can be on the order of twenty minutes for conflict detection and arrival metering applications, the focus of this study. For example, a radar, or R-side, controller is most concerned with conflict detection for time horizons on the order of five minutes in length. A planning, or D-side, controller is more concerned with conflict detection in the ten to twenty minute time horizons. In addition, trajectory prediction accuracy degrades as the time from prediction, or look-ahead time, increases. Trajectory prediction accuracy at the beginning of a trajectory's time horizon (i.e., short look-ahead time) is better than the accuracy towards the end of the time horizon (i.e., long look-ahead time). As a result, trajectory prediction accuracy should not only be measured in terms of position error, but also as a function of look-ahead time.

A trajectory prediction is calculated based on current (i.e., known) aircraft state and intent information. The intent of real aircraft, however, cannot be expected to remain constant throughout the time horizon of a trajectory prediction because of the influences of the air traffic environment (e.g., a climbing aircraft leveling off at a temporary altitude for traffic). This changing aircraft intent information makes the later portion of a trajectory prediction's time horizon invalid. Only the predicted position data for times prior to the change in intent would be valid for a trajectory prediction calculated some time earlier. Changes in aircraft intent occur unpredictably in real air traffic and will hide the true accuracy of a trajectory prediction algorithm if not factored out.

A typical trajectory prediction consists of a set of climb, level flight, and descent phases of flight. Trajectory predictions for climb and descent phases of flight are inherently less accurate than level flight predictions because modeling of aircraft performance for these phases of flight is more complex. Prediction error for a complete trajectory would likely vary depending on the phases of flight that make up that trajectory prediction. Therefore, trajectory prediction errors for each phase of flight need to be determined separately.

Trajectory prediction accuracy is affected by a number of real world uncertainties. Examples of uncertainties that contribute to trajectory prediction error include wind error, unknown aircraft thrust and weight, and track data noise. In order to derive a meaningful measure of trajectory prediction accuracy with the presence of such uncertainties, statistical analysis of trajectory prediction errors is needed. Obtaining statistically representative error measurements is a labor intensive process requiring the analysis of a large number of trajectory prediction samples. For this reason, an automated process for collecting air traffic data, factoring out unpredictable intent changes, and calculating trajectory prediction errors is required.

Previous DST research and development activities have applied various methods for measuring prediction accuracy. Cale et al, defined a generalized methodology for measuring trajectory prediction accuracy and then applied it to the analysis of trajectory predictions for en route Center controller DST.[1] Though this approach produced a general measure of trajectory prediction accuracy, the method does not distinguish trajectory prediction errors between different phases of flight (e.g., climb versus level flight) nor does it effectively account for intent changes. As a result, it is difficult to determine what parts of the trajectory prediction are causing errors. Measurements of trajectory prediction accuracy have been made under controlled field test conditions where aircraft intent is known and/or controlled.[2] Such field tests are resource intensive and are not practical on a regular basis. Other analysis of trajectory prediction accuracy using air traffic data recordings depended on analysts to manually select data samples free of intent changes.[3-5] This manual technique is not efficient for analyzing the large amounts of data that are required for a statistical analysis. An automated process for the statistical analysis of meter fix crossing times for the Center TRACON Automation System (CTAS) has been developed.[6,7] However, this approach was based on the arrival time accuracy, an indirect and incomplete measure of trajectory prediction error.

The objective of this paper is to develop an automated methodology to determine a statistical measure of trajectory prediction accuracy that is focused on the analysis of trajectory prediction algorithm performance for each phase of flight. The methodology is to be used as a tool to evaluate DST trajectory prediction accuracy, identify trajectory prediction anomalies, and facilitate improvements. Such a trajectory prediction analysis tool is vitally important for the continual development of trajectory prediction algorithms.

The paper is organized as follows. The first section is a description of the methodology, detailing the recording and analysis of the trajectory data. An evaluation of the methodology using CTAS is described in the next section. The paper closes with some concluding remarks summarizing the results of this study.

Methodology

This methodology is defined by two main processes which are designed to complement each other. The first process records the raw data required for the trajectory prediction analysis. In addition to the trajectory predictions themselves, reference or truth data for the aircraft position and altitude are recorded. Trajectory prediction errors are a function of the look-ahead time and are to be measured in terms of along track, cross track, and altitude errors relative to actual aircraft position. Actual aircraft position is determined by the radar track and altitude data recorded as the aircraft proceeds forward in time from the point at which the trajectory prediction was computed. These position data will be used as the truth data from which the trajectory prediction errors are calculated.

The second process performs the trajectory prediction error analysis of the raw radar and trajectory prediction data. In this process, unpredictable changes in aircraft intent are factored out of the data and trajectory prediction errors are calculated by phase of flight. Changes in aircraft intent are determined by analyzing the filed flight plan. A typical flight plan contains the departure and arrival airports, waypoints describing the intended horizontal path of the flight, and the planned flight altitude. The intended vertical profile of a flight is determined by assuming the aircraft will climb or descend to the planned or assigned flight altitude. Furthermore, flight categories such as departures, arrivals, and overflights can be characterized by one predominant phase of flight (i.e., climb, descent, and level flight, respectively). This categorization simplifies the search for intent changes by focusing it on one phase of flight at a time. If a deviation from the predominant phase of flight is detected in the radar track data, that would signify an intent change that could then be factored out. The process for extracting trajectory segments free of unpredictable intent changes from the recorded trajectory prediction and radar data is referred to as "segmentation" and will be described in a later section.

Trajectory Prediction Recording

It is necessary to develop a set of rules for the recording of trajectory predictions and the corresponding radar track data that would facilitate the segmentation process. The underlying premise for the trajectory prediction recording rules is that once a prediction is made, no update to the prediction is made unless there is a change in aircraft intent or phase of flight. Although a DST such as CTAS updates the aircraft's trajectory for every radar track hit (approximately 12 seconds apart), this methodology does not require this capability. For this methodology, it is necessary to hold a trajectory prediction constant for as long as it is valid, so that one trajectory prediction, with longest possible time horizon, can be used for the trajectory error measurements of each segment.

The recording of a trajectory prediction for an aircraft is initialized when the beginning of a predominant phase of flight is detected in the radar track data. For a departure, the initial trajectory prediction is recorded when the aircraft begins to climb above a minimum altitude. The start of a climb can be detected in the radar track data by observing the rate of climb. In the case of CTAS, a filtered value for rate of climb, calculated from the radar track history, is used to indicate whether an aircraft is climbing, flying level, or descending. This is referred to as the altitude status and is noted on every track hit. A minimum recording altitude of 15,000 ft is applied in this study to ensure aircraft are in the en route climb portion of their departures where maneuvering is at a minimum. The minimum recording altitude may be varied to suit the particular needs of an analysis. Similarly, recordings are initialized for overflights and arrivals when the start of level flight and descent phases of flight are detected.

Once an initial trajectory prediction is recorded for an aircraft, it is not updated until one of two events occur. One of the events that would trigger an updated trajectory prediction to be recorded is an aircraft intent change such as a flight plan amendment or temporary altitude entered into the Host computer (i.e., the computer system in the Air Route Traffic Control Center (ARTCC) that processes radar data, flight plans, and controller inputs) by an air traffic controller. An intent change invalidates the portion of the previous trajectory that had been predicted to occur after the intent change because that portion would not reflect the new intent of the aircraft. The time and altitude of the trajectory prediction update are recorded, so that the invalid portion of the previous trajectory prediction can be factored out later in the segmentation process. A delay of 36 seconds (approximately three radar track hits) is applied before the trajectory prediction is updated and recorded to allow the aircraft time to react to the new intent. This delay is also necessary because the DST may receive intent information from the Host while between trajectory prediction updating cycles.

Information regarding an aircraft's intent is not always known because such information may not be entered into the Host. For this reason, a second trajectory prediction updating trigger, independent of the Host intent information, is also used. Similar to the method by which trajectory predictions are initialized, this trigger mechanism looks for changes in the altitude status to determine if an aircraft is beginning a new predominant phase of flight segment. For example, if a departure aircraft has leveled off at a temporary altitude that has not been entered into the Host, its altitude status would indicate level flight. Level flight radar track segments for departures are not analyzed. Once the aircraft resumes its climb, the altitude status will change to indicate climbing, signifying the start of a new predominant phase of flight segment. At this point a trajectory prediction update is recorded.

Both trajectory prediction updating triggers are necessary because neither trigger alone could achieve the desired effect. There are circumstances when two trajectory prediction updates can occur in short succession. However, this is an acceptable side effect from using both rules to ensure trajectory prediction updates are not missed.

The conclusion of the trajectory prediction recording for an aircraft is flight category specific as well. For a departure, the recording concludes when the aircraft climbs to its planned flight altitude. Arrival recordings conclude when they descend to some specified altitude such as the meter fix altitude. Recording for all flight categories will conclude if the aircraft leaves the Center boundary (i.e., the outer limit of the radar data used in this study).

The resulting trajectory prediction data set for each aircraft includes information regarding the time, position, and intent of the aircraft when each trajectory prediction is recorded, and the trajectory predictions themselves. In the case of CTAS, the data set for each aircraft is stored in its own file. The radar track data for all aircraft are stored in one file. Extracting the corresponding radar data for each aircraft is done in the post recording, trajectory segmentation process.

Trajectory Segmentation

Trajectory segmentation is the second process of the trajectory analysis and is performed after the trajectory prediction data are recorded. Typical trajectory predictions contain data for time horizons that may include intent changes and segments made up of phases of flight other than the predominant one. In the segmentation process, segments made up of the predominant phase of flight are extracted from the trajectory prediction and radar track data recordings. Specific criteria are applied to factor out intent changes from the data segments before error calculations are performed.

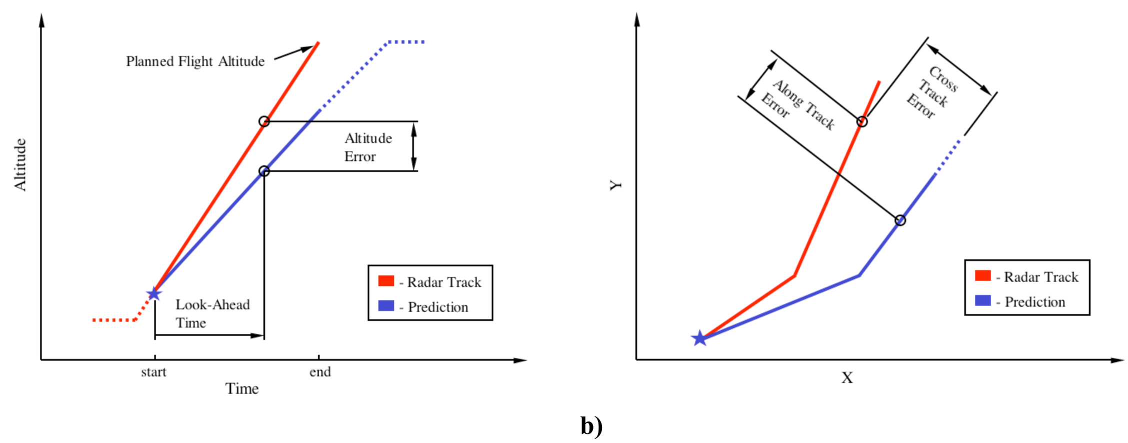


Figure 1: Climb segmentation for a departure. a) Vertical profile b) Horizontal profile

An example of a simple departure profile in which an aircraft climbs to its planned flight altitude before starting its level flight cruise leg is shown in Fig. 1. In this example, data for a single trajectory prediction are shown with the prediction start point represented by a star. The recorded radar track data for the same aircraft are also shown. For a departure, the segmentation process extracts only the climb segment from the trajectory prediction and radar track data. The segmentation process truncates each set of data such that the segments will have the same start and end times. The resulting segments to be used for the error calculations are represented in Fig. 1 by the solid portion of each respective line. The start time for a segment is the time the recorded trajectory prediction is actually calculated. Since CTAS calculates trajectories at each radar track hit, the segment start time and the first radar track time of the segment are the same.

Table 1. Segment End Time Criteria

Phase of Flight	Segment Ending Events for Trajectory Prediction Data	Segment Ending Events for Radar Track Data
Climb	predicted altitude >= trajectory update altitude predicted altitude >= end-of-recording altitude predicted altitude >= temporary altitude	track altitude >= trajectory update altitude track altitude >= end-of-recording altitude track altitude >= temporary altitude track altitude status ≠ climb
Level Flight	None	track altitude status ≠ level
Descent	predicted altitude <= trajectory update altitude predicted altitude <= end-of-recording altitude predicted altitude <= temporary altitude	track altitude <= trajectory update altitude track altitude <= end-of-recording altitude track altitude <= temporary altitude track altitude status ≠ descent
All	predicted time >= trajectory update time predicted time >= end-of-recording time	track time >= trajectory update time track time >= end-of-recording time

The segment end time is determined by event-driven criteria based on the phase of flight of the trajectory segment being analyzed. These criteria are summarized in Table 1. Both the radar track and trajectory prediction data are searched for segment ending events. The time corresponding to the first occurrence of any segment ending event in either the trajectory prediction or radar track data marks the end of that particular segment.

The first segment ending event for the example shown in Fig. 1 occurs when the radar track altitude is equal to the end-of-recording altitude (i.e., planned flight altitude for departures). The resulting segment end time is the time corresponding to this event. The same segment end time is applied to both radar track and trajectory prediction data of the segment. Consequently, the trajectory prediction data are truncated at this time, prior to that data actually reaching the planned flight altitude. This example is characteristic of an aircraft with an actual rate of climb greater than the predicted rate.

Flights with multiple segments can also occur. In the arrival example shown in Fig. 2, the descending aircraft levels off at a temporary altitude before completing its final descent. Two trajectory predictions are recorded in this example, which correspond to the beginning of each of the two descent segments. The first segment ending event occurs when the predicted altitude is equal to the temporary altitude. The radar track data for segment one are truncated at the same end time, before the temporary altitude is reached.

The second segment in Fig. 2 illustrates a trajectory prediction anomaly. A level flight leg is predicted to occur in the trajectory before the descent leg, even though the actual aircraft is descending. Based on the segment end time criteria, the second segment ends when the radar track altitude is equal to the end-of-recording altitude (i.e., minimum recording altitude for arrivals). The trajectory prediction data are truncated at this time, but the level flight leg remains. This level flight anomaly will manifest itself as an altitude error when the trajectory prediction errors are calculated for the segment.

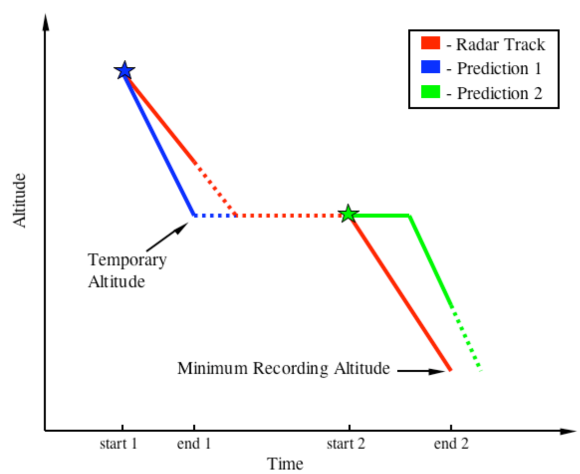


Figure 2: Arrival with multiple descent segment

Trajectory Prediction Errors

The trajectory prediction errors are calculated for each radar track point in a segment. These errors are a function of look-ahead time. The look-ahead time is measured from the segment start time to a radar track point as illustrated in Fig. 1. The corresponding trajectory prediction point is obtained by interpolating the trajectory prediction data for the same look-ahead time. Altitude, along track, and cross track errors are calculated with the following equations:

$$\text{Altitude Error} = \text{Altitude}_p - \text{Altitude}_t \tag{1}$$

$$\Delta X = X_p - X_t$$

$$\Delta Y = Y_p - Y_t$$

$$\text{Along Track Error} = \Delta X \sin \Psi_p + \Delta Y \cos \Psi_p \tag{2}$$

$$\text{Cross Track Error} = \Delta X \cos \Psi_p - \Delta Y \sin \Psi_p \tag{3}$$

The radar track point and its corresponding trajectory prediction point are indicated by subscripts t and p, respectively. Along track error, Eq. (2), is measured parallel to the predicted course, Ψ_p. Cross track error, Eq. (3), is measured perpendicular to the predicted course. The predicted course was used in the error equations because estimated course derived from the radar track data was noisy.

The altitude errors for the example in Fig. 2 are shown in Fig. 3. The duration of each segment typically differs, resulting in a decreasing number of samples as the look-ahead time increases. For the analyst-selected look-ahead times (T_0, T_1, etc.), error data are compiled for each segment. Data from a number of segments are necessary to obtain a statistically representative number of samples, especially for the larger look-ahead times. In this example, Prediction 1 does not contribute a sample for look-ahead time T_4. Error samples for each segment are compiled as a function of look-ahead time and presented in a histogram format. Along track and cross track errors are presented in the same manner.

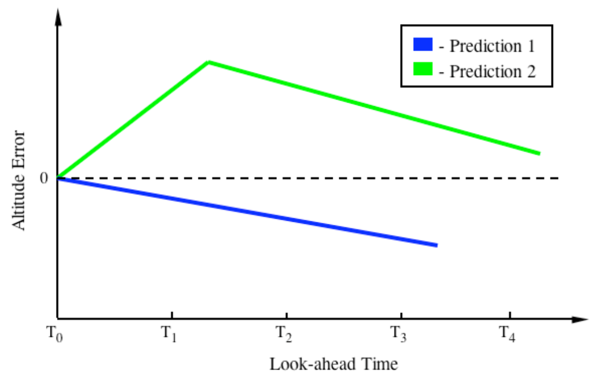


Figure 3: Altitude error versus look-ahead time

Data Outlier Limits

Data outliers are identified by establishing limits on the calculated altitude, along track, and cross track errors. By analyzing the data collected for this study, reasonable error limits were determined. Calculated errors greater than these limits can be attributed to aircraft that were clearly deviating from their trajectories for unpredictable reasons. The limits are a function of phase of flight. Trajectory segments with a calculated error outside of any one of the limits shown in Table 2 were excluded from all segment statistics.

Table 2. Trajectory Outlier Limits

	Phase of Flight	
	Climb/Descent	Level Flight
Along Track (nm)	± 10	± 20
Cross Track (nm)	± 5	± 5
Altitude (ft)	± 5000	± 1000

The majority of the exclusions were due to large cross track errors. This was attributed to aircraft deviating from their filed flight plan route. It is not uncommon for aircraft to fly off their flight plan route. Aircraft intent information is a vital component of a trajectory prediction and must be entered into the Host for it to be processed by the prediction algorithm. Because these types of route deviations are not entered into the Host, it is not possible to make valid trajectory prediction for these aircraft. Therefore, these segments were excluded from the error statistics.

Methodology Evaluation

The goal of this evaluation was to demonstrate that the methodology was capable of making statistical measurements of trajectory prediction accuracy with enough sensitivity to facilitate improvements to the trajectory prediction algorithm. A series of accuracy measurements were conducted using the baseline trajectory prediction algorithm. Based on the results of these measurements, the trajectory algorithm or the aircraft performance model was refined, and a second round of measurements were conducted to confirm any improvements.

The trajectory analysis methodology was evaluated on the NASA-developed CTAS with radar track data from the Fort Worth ARTCC (ZFW). CTAS software version dated October 27, 2003 was used as the baseline for the evaluation. Trajectory prediction recording functionality was implemented into the existing data recording features of CTAS. The post recording, trajectory segmentation process was implemented with a combination of Perl and Matlab scripts.

Approximately eighteen hours of radar data were collected over five different days between June and August 2003. Weather data for the same period were also saved. The data for this evaluation were limited to large commercial jet aircraft flights (e.g., Airbus, Boeing) totaling 800 departures, 1,168 overflights, and 806 arrivals. Flight categories in ZFW are defined relative to the primary airports in the Center, Dallas-Fort Worth (DFW) and Dallas-Love Field (DAL). This data set was consistently used for all analysis in this evaluation.

Level Flight Trajectories

Level flight data from overflights were used for the initial methodology evaluation. Trajectory prediction recording for an overflight was initiated when the altitude status first indicated level flight. This could occur immediately after the first radar track hit. Along track and cross track error histograms for segments with look-ahead times of fifteen minutes, calculated with the baseline trajectory prediction algorithm, are shown in Fig. 4.

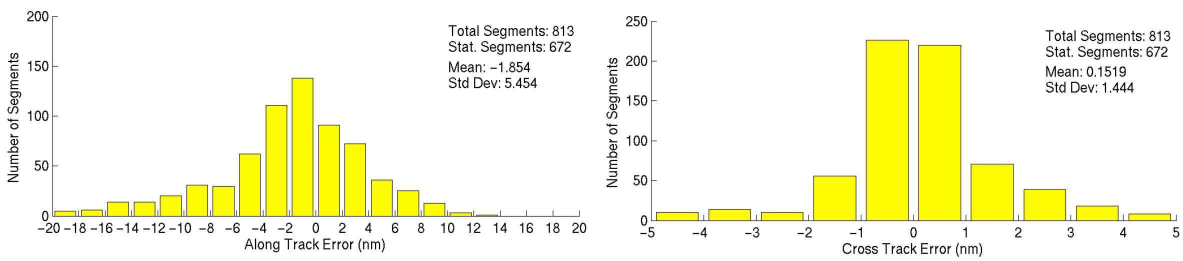


Figure 4: Baseline level flight trajectory errors for a look-ahead time of 15 minutes

The total number of level flight segments with data for a look-ahead time of fifteen minutes was 813, including outliers. Approximately 17 percent of the segments were excluded from the statistics based on the limits defined in Table 2. The mean and standard deviation for the along track error of the remaining 672 segments were -1.9 nm and 5.5 nm, respectively. Cross track error mean and standard deviation were 0.15 nm and 1.4 nm. Analysis of the along track and cross track histograms indicate the outlier limits were not so stringent as to affect the error distributions. Excluded segments were more than three times the standard deviation (3σ) from the mean.

A more detailed investigation of individual flights on the "fringes" of the along track error distribution revealed that ground speed error contributed directly to the increased along track error. Horizontal position and ground speed data for a representative flight (COA1711) are shown in Fig. 5.

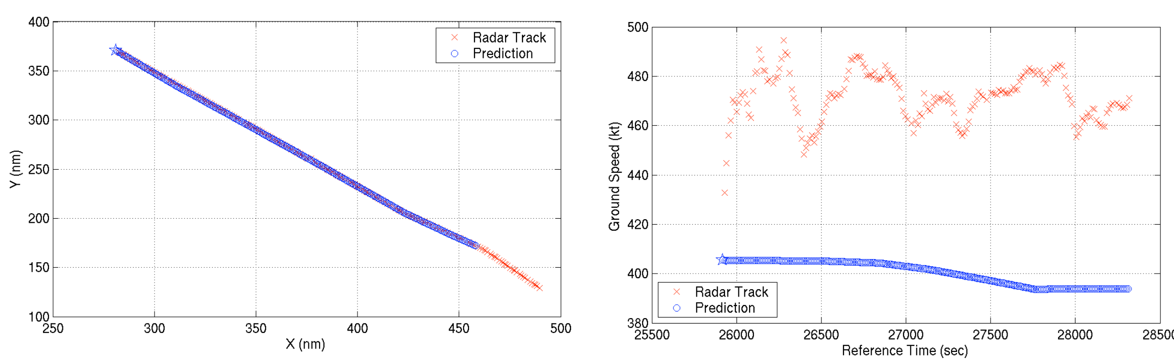


Figure 5: Horizontal position and ground speed predictions for COA1711

The ground speed data are plotted versus a system reference time. The corresponding along track error for the first twenty minutes of the segment is shown in Fig. 6. For a fifteen minute look-ahead time, the along track error is approximately -20 nm. The predicted trajectory for COA1711 had negligible cross track error and altitude error.

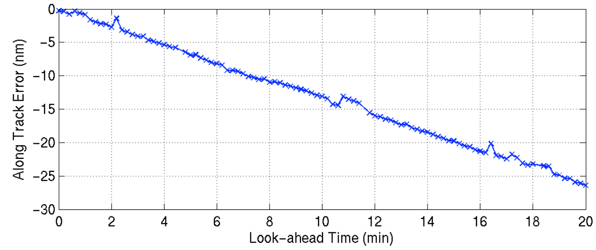


Figure 6: Along track error for COA1711

The airspeed used for level flight trajectory predictions is highly dependent on predicted winds and the ground speed at the time of prediction. In this case, a ground speed of approximately 405 knots, determined from the third radar track hit, was used to derive the airspeed for the trajectory prediction. This value is clearly slower than the ground speed for subsequent radar tracks. Accordingly, the resulting trajectory prediction errs on the slow side, leading to a large negative along track error (Eq. 2).

For CTAS, ground speeds for the first two radar tracks are initialized with ground speed values directly from the Host. The first two ground speed values for COA1711 were initialized with the relatively low values of 235 knots and 356 knots. Ground speeds for subsequent radar tracks are calculated from position data. Because ground speed is calculated from noisy position data obtained from the Host, a filter is applied by CTAS to smooth the ground speed values. It takes approximately ten radar tracks for the filter to effectively stabilize the initial ground speed calculations.

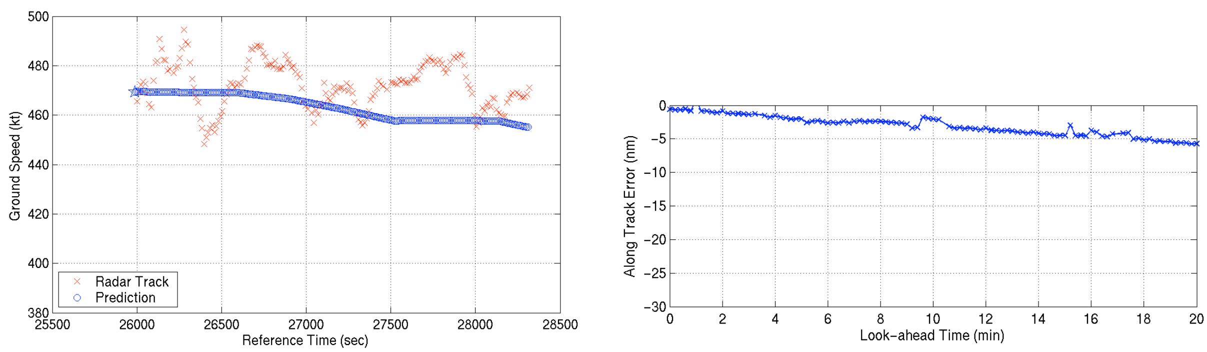


Figure 7: Ground speed prediction and along track error with ground speed filter delay for COA1711

In order to get a more accurate measurement of the trajectory prediction error, the CTAS trajectory prediction recording software was changed so that no trajectory prediction was recorded until ten radar tracks have been received for a given aircraft, minimizing the influences of poor quality ground speed data from the Host. The ground speed and along track error plots for COA1711 with the ground speed filter delay are shown in Fig. 7. The trajectory prediction was calculated based on an airspeed derived from a ground speed of approximately 469 knots, a value more representative of the subsequent radar tracks. The corresponding along track error for a look-ahead time of fifteen minutes decreased from -20 nm to -5 nm. Although the along track error was not zero, a significant source of error has been accounted for.

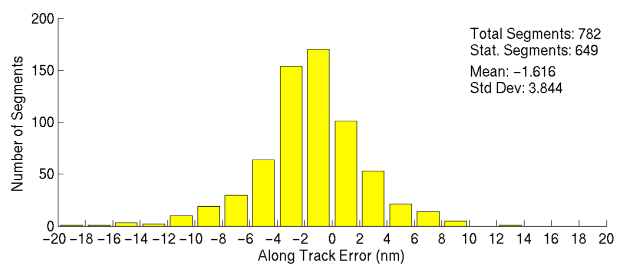
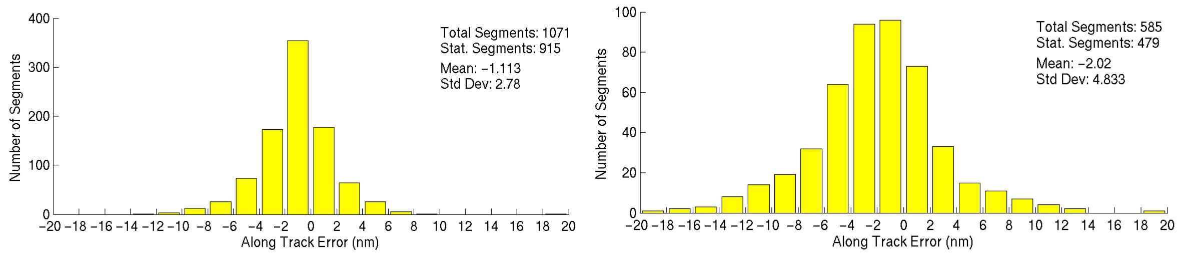


Figure 8: Level flight along track errors with ground speed filter delay for a look-ahead time of 15 minutes

This ground speed filter delay was applied to the entire data set and the trajectory predictions were recalculated. The resulting histogram, shown in Fig. 8, demonstrates the sensitivity of the error measurements made with this methodology. The effects of a small change that influences the trajectory prediction algorithm were detected. Note the reduction of error at the fringes of the distribution. The standard deviation of the along track error for a fifteen



a) b)

Figure 9: Level flight along track errors with ground speed filter delay for look-ahead times of: a) 10 minutes and b) 20 minutes

minute look-ahead time was reduced from 5.5 nm to 3.8 nm. The number of statistical segments was reduced because those level flight segments affected by the ten track delay were up to two minutes shorter. Therefore, some segments no longer reached a look-ahead time of fifteen minutes.

Trajectory prediction errors for other look-ahead times were also evaluated. Along track error histograms for look-ahead times of ten minutes and twenty minutes are shown in Fig. 9. Generally, the longer the look-ahead time, the fewer the segments that are available and the greater the prediction uncertainty. Standard deviation of the along track error increases from 2.8 nm for a look-ahead time of ten minutes to 4.8 nm for a look-ahead time of twenty minutes.

Climb Trajectories

Climb trajectory prediction error analysis was conducted with departure data. Prediction time horizons for climb data are inherently shorter than that of level flight data because only the climb portion of the departure trajectory prediction is analyzed. Climb trajectory prediction error histograms for a look-ahead time of five minutes are shown in Fig. 10. Climb data outliers were excluded from the statistical segments based on the limits defined in Table 2. All but two outliers were attributed to excessive cross track error. The other two outliers were due to excessive altitude error. As with the level flight outlier limits, climb outlier limits were large enough so that the general error distributions were not affected.

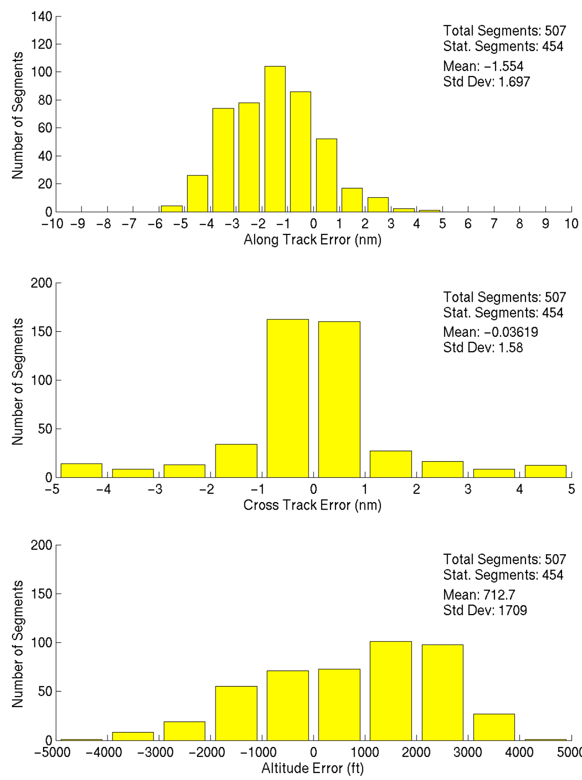


Figure 10: Climb trajectory prediction errors for a look-ahead time of 5 minutes

Climb trajectory predictions are more sensitive to aircraft performance model information than level flight predictions. The data set used in this analysis contained a number of different large jet aircraft types. The wide distribution of altitude errors about the mean suggest that the trajectory predictions for some aircraft types were better than others.

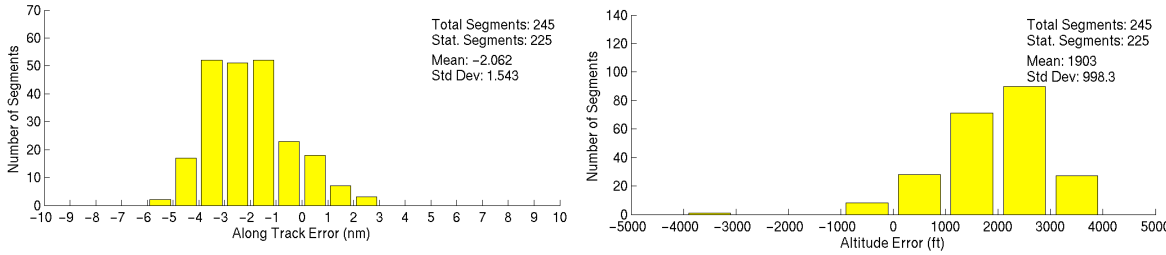


Figure 11: MD80 climb trajectory prediction errors for a look-ahead time of 5 minutes

A more detailed analysis of the aircraft types in this data set revealed 225 of the 454 statistical segments were from MD80 aircraft. This was not unexpected because DFW is an airport hub for American Airlines, a major user of MD80 aircraft. Along track and altitude error histograms with only the MD80 segments are shown in Fig. 11. The MD80 altitude error distribution was not as widely distributed about the mean. The standard deviation was 998 feet compared to 1709 feet for the complete data set. The MD80 histogram clearly showed the predicted rate of climb was higher than the actual rate, resulting in a large positive altitude error (Eq. 1). The mean MD80 along track error indicated the predicted position of the aircraft was behind the actual position.

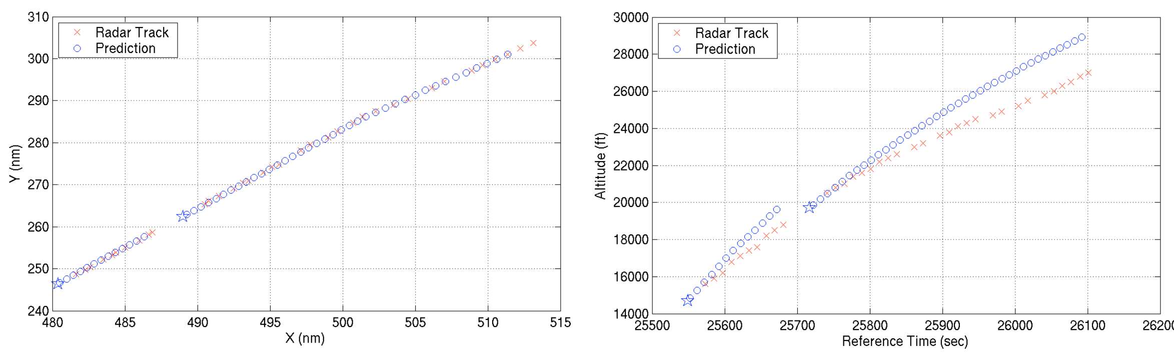


Figure 12: Radar track vs. trajectory prediction for AAL326

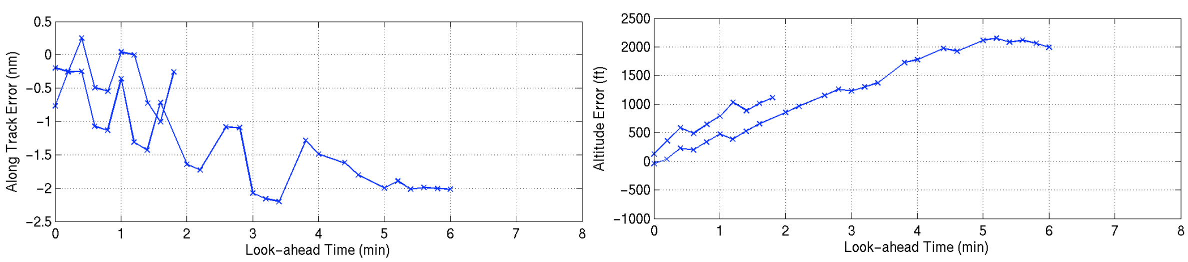


Figure 13: Trajectory prediction errors vs. look-ahead time for AAL326

Radar track data and the corresponding trajectory predictions for a single, representative MD80 flight (AAL326) are shown in Fig. 12. The altitude data are plotted versus a system reference time. In this example, there are two climb segments, the initial trajectory followed by a trajectory update due to a flight plan amendment. Along track and altitude errors as a function of look-ahead time for AAL326 are shown in Fig. 13. Trajectory prediction errors at a look-ahead time of zero are partially due to the asynchronous nature of the trajectory calculation and recording processes within CTAS and are currently being addressed with planned software improvements. For the purpose of this methodology evaluation, it was not necessary to factor out these initial errors.

Improvements to the MD80 climb trajectory prediction accuracy were sought by adjusting weight, thrust, and speed parameters in the aircraft performance model within CTAS. A process of adjusting performance model parameters followed by recalculating the trajectories for three to five representative flights was performed until the trajectory errors approached zero. In this case, the thrust multiplier was reset from 2.3 to the nominal value of 2.0.

With a nominal thrust multiplier applied, climb weight adjustments were used as the primary means of reducing altitude error, while climb speed adjustments were used to reduce along track error. Climb weight was reduced from the default value based on 90% of the maximum takeoff weight of 147,000, or 132,300 lb, to 121,500 lb. Climb speed was increased from 280 knots to 300 knots. The resulting trajectory prediction errors with the adjusted model parameters for AAL326 are shown in Fig. 14. The along track errors and the altitude errors have been reduced. For a look-ahead time of five minutes, the along track error decreased from approximately -2 nm to -0.4 nm. Altitude error decreased from approximately 2,100 feet to 600 feet for a look-ahead time of five minutes.

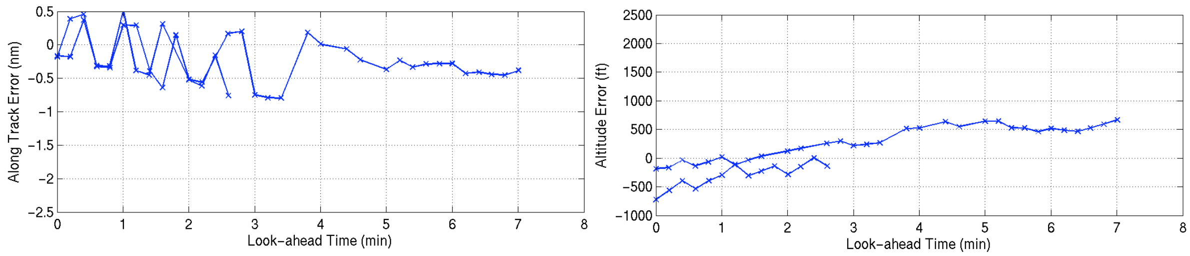


Figure 14: Trajectory prediction errors with adjusted model for AAL326

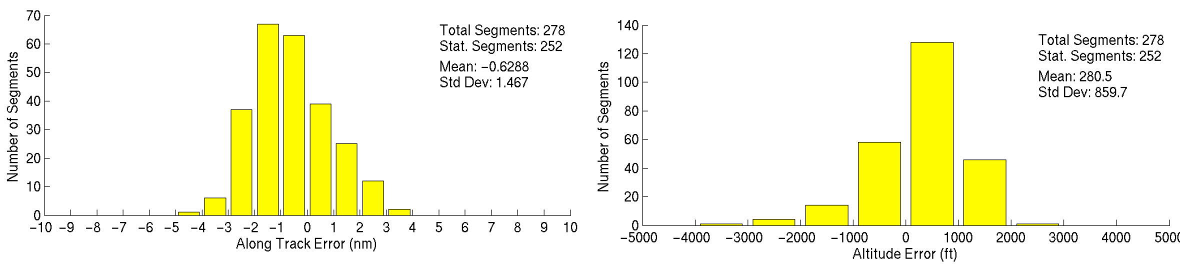


Figure 15: MD80 climb trajectory prediction errors with adjusted model for a look-ahead time of 5 minutes

These model parameter changes were then applied to all the MD80 flights. The resulting trajectory error histograms are shown in Fig. 15. The mean altitude error was reduced from 1903 feet to 281 feet, while the mean along track error was reduced from -2 nm to -0.6 nm. The number of statistical segments in the adjusted MD80 histograms increased, although the same data set was analyzed. Because the predicted climb rate was reduced, climb segment time horizons increased. This is evident when comparing segment lengths in Fig. 13 to those in Fig 14. As a result, more climb segments reached a look-ahead time of five minutes.

The model parameters for Boeing 737 and 757 types were adjusted in a similar manner. These aircraft types, together with the MD80, represent approximately 84 percent of the departures in this data set. The error histograms for a look-ahead time of five minutes for all large jet aircraft are shown in Fig. 16. Comparison of histograms in Fig. 10 with those in Fig. 16 demonstrates that this methodology can effectively reveal improvements in the overall climb trajectory prediction accuracy. The mean along track error has decreased from –1.6 nm to –0.6 nm. The mean altitude error has decreased from 713 ft to 36 ft. Altitude error distribution for the adjusted models became more normal, with standard deviation decreasing from 1,709 feet to 1,180 feet.

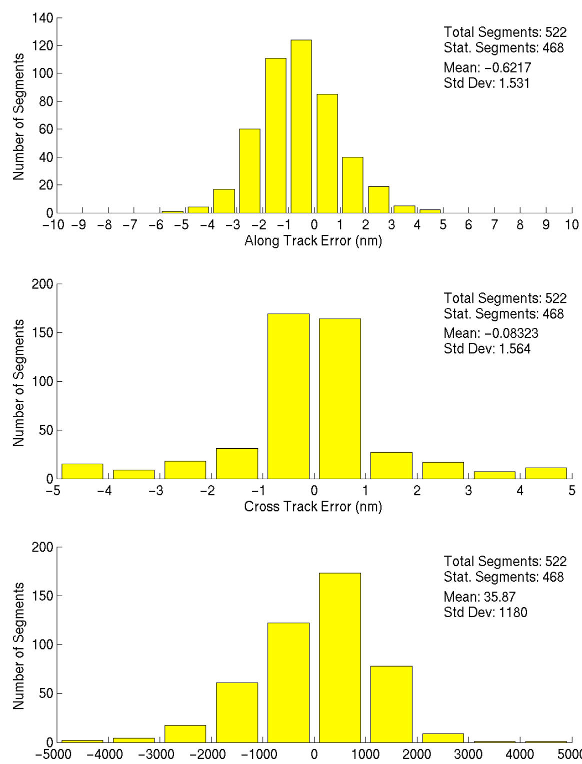


Figure 16: Climb trajectory prediction errors with adjusted models for a look-ahead time of 5 minutes

Descent Trajectories

Descent trajectory prediction accuracy for the vertical profile was found to be affected by trajectory prediction anomalies. An altitude error histogram for descent trajectories, with a look-ahead time of two minutes, exhibits an abnormal error distribution and is shown in Fig. 17. Mean altitude error for descent trajectories with a look-ahead time of two minutes is 498 feet with a standard deviation of 2,245 feet. This wide error distribution about the mean is characteristic of undesirable trajectory algorithm performance.

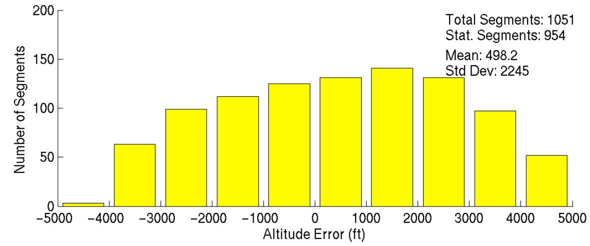


Figure 17:Descent altitude errors for a look-ahead time of 2 minutes

A more detailed analysis of individual flights revealed anomalies with the building of trajectories for flights with temporary altitudes. The radar track plot and the corresponding altitude error plot for a representative arrival flight (AAL1602) with these temporary altitude anomalies are shown in Fig. 18 and 19. The first segment for AAL1602 is a descent from the planned flight altitude to a temporary altitude of 24,000 ft. This segment is followed by a descent to the meter fix altitude of 11,000 ft, which is entered by a controller into the Host as a temporary altitude. Descents to two temporary altitudes prior to entering TRACON airspace are typical of ZFW arrivals.

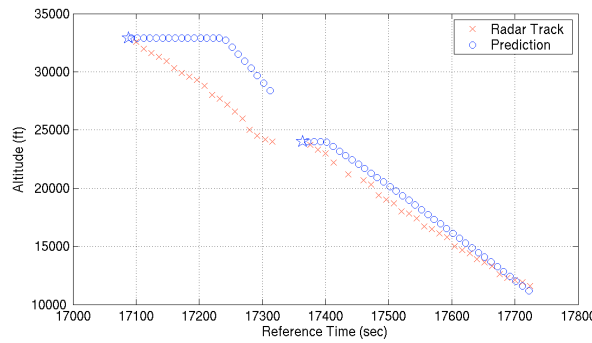


Figure 18: Radar track vs. trajectory prediction for AAL1602

The actual aircraft track is descending in both segments. The trajectory segments resulting from the recording and segmentation rules for arrivals should have yielded descent trajectories for each trajectory segment. However, each segment clearly begins with a level flight leg. These anomalies manifest themselves as altitude errors, as shown in Fig. 19. For a look-ahead time of two minutes, the errors are approximately 5,000 feet and 1,500 feet.

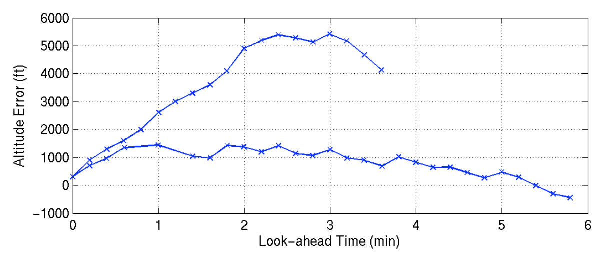


Figure 19: Altitude error vs. look-ahead time for AAL1602

There are two specific parts of the CTAS software that affect the processing of temporary altitudes for arrival trajectory predictions, in this case. The first part was in effect for the first segment shown in Fig. 18. If the level flight segment at a temporary altitude was predicted to be less than fifteen nautical miles, an inadvertent error condition was created, causing the temporary altitude to be ignored. As a result, a nominal arrival trajectory was built by the trajectory prediction algorithm that consisted of a level flight segment followed by an idle thrust descent segment, direct to the meter fix (i.e., bypassing the temporary altitude). If the actual aircraft is descending, as in this case, the desired trajectory is an immediate descent and level off at the temporary altitude, regardless of the length of the level flight segment at that temporary altitude, followed later by a descent to the meter fix. Radar track data shows that the actual aircraft follows this trajectory.

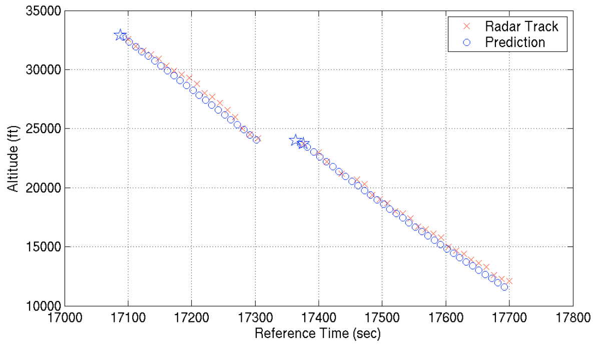


Figure 20: Radar track vs. corrected trajectory prediction for AAL1602

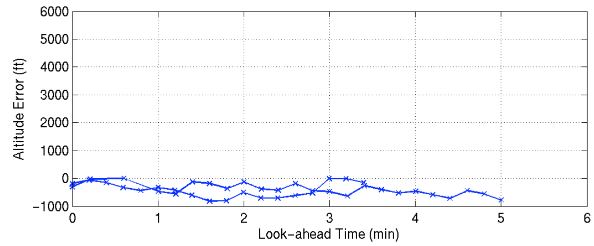


Figure 21: Altitude error vs. look-ahead time for AAL1602 with corrected trajectory prediction

The other part of the temporary altitude processing software affects the second segment. This part of the software caused a nominal arrival trajectory to be predicted if the temporary altitude was the same as the meter fix altitude. As with the first segment, the actual aircraft was descending to the temporary altitude at the time the predicted trajectory was computed. Therefore, the trajectory prediction should start with a descent segment to the temporary altitude instead of starting with the level flight segment. Changes to the trajectory prediction algorithm were made to correct these temporary altitude anomalies. The resulting radar track and altitude error plots for AAL1602 are shown in Fig. 20 and 21. Both trajectory predictions now begin with descent segments, not unlike the actual aircraft trajectory. As a result, trajectory prediction error has been reduced.

These trajectory prediction algorithm corrections were then applied to the entire data set. The resulting altitude error histogram for descent trajectories with a look-ahead time of two minutes is shown in Fig. 22. The altitude error distribution is not as widely distributed about the mean as in Fig. 17, an indication of improved trajectory prediction algorithm performance. Standard deviation has been reduced from 2,245 feet to 1,813 feet. The mean altitude error changed from 498 feet to –842 feet. Additional improvements to the accuracy of CTAS descent trajectory predictions have been made, but were not presented as part of this methodology evaluation.

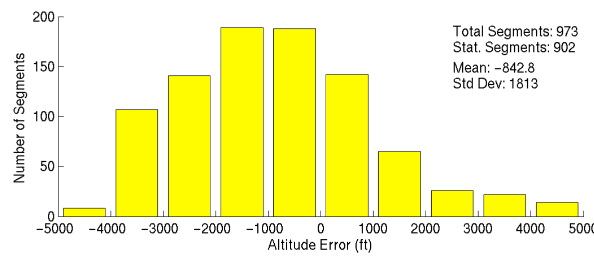


Figure 22: Descent altitude errors with corrected trajectory predictions for a look-ahead time of 2 minutes

General Limitations

The general limitations to the accuracy measurements of this methodology can be classified into two categories, air traffic data source biases and sampling. As might have been expected, the applicable scope of the trajectory prediction accuracy measurements was dependent on the air traffic data source, in this case, ZFW. The presence of biases in the data source will affect the generalization of the accuracy assessment. For example, improvements to the Boeing 757 climb trajectory prediction accuracy due to adjustments to the climb weight may not be realized in the Oakland ARTCC, which includes heavier transcontinental and extend over-water flights not typically present in ZFW. Wind model biases may also be present in the data. Although random wind errors, as well as other errors, are accounted for by using a statistical analysis, biases will not be. Overall accuracy assessments should only be made in the context of the air traffic found in the data source. Additional data would need to be analyzed in order to obtain a broader accuracy assessment.

Limitations due to sampling were directly related to the rules established for the trajectory prediction recording and segmentation processes. Although these rules facilitate automation, current rules have limited the types of trajectory predictions analyzed. For example, low speed, level flight trajectory predictions associated with arrival flight metering were not analyzed. Current recording and segmentation rules only considered the relatively high speed, level flight trajectory predictions of overflights. Additional recording and segmentation rule need to be developed so that a wider range of trajectories can be analyzed.

Conclusion

The technical changes that can be implemented to improve DST trajectory prediction accuracy are widely understood. However, an efficient and effective method for performing statistical analysis and measurements of trajectory prediction accuracy using real air traffic data has not been universally adapted. The ability to measure improvements, or lack thereof, to the trajectory prediction algorithms against real air traffic is a fundamental necessity for continual DST development. For this reason, a methodology for automated trajectory prediction analysis was developed.

The methodology is based on rules that were automated to record, segment, and remove outliers from trajectory data. The automated, trajectory segmentation process factored out unpredictable changes in aircraft intent that affected trajectory prediction accuracy measurements. This methodology facilitated the analysis of large, statistically representative amounts of data, resulting in meaningful and versatile trajectory prediction error measurements.

The methodology evaluation demonstrated the versatility of the trajectory prediction error measurements. These error measurements were sensitive to small trajectory prediction algorithm changes. Overall trajectory prediction accuracy was assessed as well as trajectory accuracy improvements due to aircraft performance model changes. Analysis of the error histogram distributions created with this methodology was used to effectively identify trajectory prediction anomalies. Once an anomaly was identified, the same methodology was applied to evaluate the effectiveness of any subsequent algorithm changes. This methodology has proven to be an effective, labor saving new medium for facilitating improvements to CTAS trajectory prediction accuracy, and therefore, DST performance.

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