Using Air−Ground Data Link to Improve Air Traffic Management Decision Support System Performance

Craig Wanke

The MITRE Corporation
Center for Advanced Aviation System Development
1820 Dolley Madison Boulevard, M.S. W297
McLean, VA USA 22102

Abstract

Decision support systems (DSS) are being developed for many air traffic management (ATM) applications. Examples include conflict detection, conflict resolution, evaluation of user reroute requests, and flow management. Many applications require that the DSS compute and maintain a database of predicted aircraft trajectories. The usefulness of these systems, and hence their capability to provide benefits to airspace users, is strongly dependent on the accuracy of predicted trajectories. Although current prototypes achieve adequate trajectory prediction accuracy using available information, deficiencies in the available information set limit achievable prediction accuracies. Improved prediction accuracy may enable development of more advanced ATM DSS, providing greater benefit to airspace users.

This paper describes a study evaluating the use of aircraft speed and wind reports via data link to improve trajectory prediction. Aircraft reports collected in the field were used to develop a model for trajectory prediction errors due to airspeed and wind variations. Incorporation of these reports into a prototype DSS was found to significantly improve trajectory prediction accuracy and stability.

Keywords: ATM automation, aircraft trajectory modeling, conflict detection, air−ground data link

1. Introduction

Over the next decade, the Federal Aviation Administration (FAA) plans to upgrade decision support systems (DSS) for its operational personnel. These systems will aid in detection of aircraft−to−aircraft conflicts and conflicts with special use airspace (SUA), in scheduling use of National Airspace System (NAS) resources such as airports and congested airspaces, and in managing traffic flow under constrained circumstances such as the presence of hazardous weather. These systems will all depend on the ability to predict the future trajectories of aircraft, with varying degrees of accuracy and look−ahead time depending on the specific application.

Prototypes of such systems have been fielded at various FAA facilities. These include the User Request Evaluation Tool (URET) at the Indianapolis Air Route Traffic Control Center (ARTCC) and the Center−TRACON Automation System (CTAS) at the Denver ARTCC. The tools provided by these prototypes depend on predicted aircraft trajectories, which in turn depend on a set of data provided by the existing NAS infrastructure. This data set includes flight plans, radar surveillance data, and configuration data such as the current airspace sectorization plan. These are supplemented by wind forecasts, airspace adaptation data from a variety of sources, and by tool−specific configuration data used to model aircraft performance and the impact of current ATC procedures and restrictions on aircraft flight paths.

These data, although well−suited to currently−fielded operational ATC and flow management systems, lack some information which limits the accuracy of aircraft trajectory predictions. For example, current flight plans do not contain some potentially useful aircraft performance information such as aircraft weight. Current radar surveillance reports do not contain some aircraft−specific information such as airspeed and the current wind conditions. While URET, for example, has demonstrated operationally acceptable performance with currently available data, better trajectory prediction may be desirable or necessary for the next generation of decision support tools. This may be achievable by obtaining supplementary data to address the weaknesses in the current data set. This study specifically addresses the use of air−ground data link to compensate for the lack of accurate airspeed and wind data in the existing data set.

2. Background

2.1 .Data Sources for En Route Tools

Current enroute DSS prototypes (URET, CTAS) obtain flight plans and radar surveillance data from the ARTCC Host Computer System (HCS), and wind forecast information from the U.S. National Oceanic and Atmospheric Administration (NOAA). A MITRE installation at the Kansas City ARTCC also has access to Aircraft Communications Addressing and Reporting System (ACARS) connection, though which direct reports from aircraft can be received. All of these data sources are being used in this study, and are described briefly below.

Radar Surveillance Data. Aircraft positions and velocities ("track reports") are derived by the HCS from radar surveillance data, which is received on a 12−second cycle. Radar reports provide a measurement of position and altitude (via Mode C transponder replies). An alpha−beta tracker is used to provide smoothed position, groundspeed, and heading data. These data provide the means for updating flight progress along the predicted trajectory and monitoring conformance to the flight plan.

One limitation of the track reports is that due to the finite temporal and spatial resolution of the radar reports, the estimated groundspeed and heading is somewhat noisy, and responds slowly to changes in the actual speed and heading of the aircraft. Although the results are adequate for display to the controller, the noise and lag characteristics can complicate the task of trajectory prediction and conformance monitoring. This is one of the chief areas in which air−ground data link reports can improve modeling, by providing accurate speed information.

Flight Plans. Flight plans are received from the HCS at some parameterized time before the ARTCC will likely begin processing the flight, either due to a handoff from an adjacent facility or due to an internal departure. This time is typically around 30 minutes. Flight plans include the route of flight, coordination fix and time, intended cruise airspeed, assigned altitude, aircraft type, aircraft navigation equipage, and some other supporting details. Flight plan amendments are received when input by the sector controllers.

One problem with using HCS flight plans for trajectory prediction is the lack of aircraft performance−related information. For example, although the aircraft type is given, the takeoff weight is not. This is most critical in the climb phase of flight, when the aircraft rate−of−climb can vary as much as a factor of 2 between light and heavy takeoff weights. This provides motivation for obtaining additional flight planning data from aeronautical operational control centers (AOCs), the second part of this study and the subject of a future report.

Meteorological Data. The URET and FFES tools currently use the Rapid Update Cycle (RUC) weather forecast product developed by the NOAA Forecast Systems Laboratory and implemented at the National Centers for Environmental Prediction (NCEP) Environmental Modeling Center. RUC provides forecasts of winds, temperatures, and pressures over the conterminous United States at a spatial resolution of 60km and at 25 altitude levels. These forecasts are made 8 times per day based on a wide variety of sources, ranging from Doppler radar to ACARS reports. A separate forecast grid is generated for each hour of the day. Due to computation and distribution times, the end result is that an hourly forecast between 3 and 6 hours old is available for any hour of the day. The next version of RUC, currently under development, will improve resolution (to 40km spatially and 40 altitude levels), timeliness, and content of the data.[1]

ACARS Data Link. The Aircraft Communications Addressing and Reporting System (ACARS). developed and maintained by ARINC, is the only aeronautical data link currently in widespread use in the U.S. It is a character−based system primarily used for airline operational communications between ground facilities and aircraft such as departure and arrival times, connecting gate information, and other airline−specific data. Some aircraft also use ACARS to periodically and automatically downlink progress reports, which typically include position, altitude, speed, winds, and heading information. These progress reports were used in this evaluation to provide input to the trajectory prediction algorithms. Note that no form of air−ground data link is currently being used by the prototype systems under controller evaluation − CTAS and URET − although both systems are designed with the intent of using data link in the future.

2.2 The User Request Evaluation Tool

The User Request Evaluation System has been developed as a first step in the incremental deployment of decision support tools to the field. In the United States as elsewhere, user demand for airspace system resources continues to grow and is forecast to continue increasing. In order to both meet increased demand and maintain safety with current ATC systems, delays and restrictions must be imposed on airspace users. Restrictions of any kind increase the operating costs of airspace users. Therefore, URET provides a set of decision support capabilities which can increase the efficiency of controllers by decreasing the amount of time required to identify and resolve problems. As the system becomes more efficient, restrictions can be removed and the cost to users of those restrictions lessens. The removal of such restrictions is a key element of the "free flight" concept, in that it provides users more flexibility in filing flight plans that fit their specific needs. URET provides the following tools:

• Early detection of aircraft−to−aircraft and aircraft−to−airspace separation problems.

• Resolution aids ("trial planning") which allow quick evaluation of possible solutions as well as user−requested reroutes for potential problems.

• A Computer−Human Interface (CHI) which provides an effective interface to the problem detection and resolution tools.

URET was delivered to the Indianapolis ARTCC (ZID) in January 1996, and has undergone a series of evaluations with controllers. These evaluations have been used to determine the usability of the systems in general as well as analysis of the performance of the underlying algorithms. Generally, controllers found URET to be a significant improvement for both strategic planning and decision making applications, and found the performance of the problem detection algorithms to be satisfactory. A detailed description of the evaluation results is available in Reference 2.

2.3 The Free Flight Evaluation System

The Free Flight Evaluation System has been developed by CAASD to explore candidate concepts and technologies which can enable "free flight". The FFES is installed at the Kansas City ARTCC (ZKC) and operates in a parallel, non−interfering mode with normal ZKC operations. The core algorithms of the system − comprising track management, plan management, and trajectory modeling functions − are based on the currently−fielded URET capabilities. However, extensions have been made to support a wide variety of experiments. The FFES has been used to prototype ATM decision support tools for conflict detection and flow management, to explore concepts for collaboration between airspace users and air traffic management personnel, and to support flight tests of a proposed Automatic Dependent Surveillance−Broadcast (ADS−B) and Flight Information Service−Broadcast (FIS−B) system.

Figure 1 illustrates the configuration of the FFES at ZKC. To support this study and the experiments noted above, the FFES has connections to many information sources and data paths. For this study, HCS, ACARS, and meteorological data were recorded over the space of several months. The data were then analyzed and processed by the FFES trajectory modeler to produce the results described below. More detail on the FFES and associated experiments is available in Reference 3.

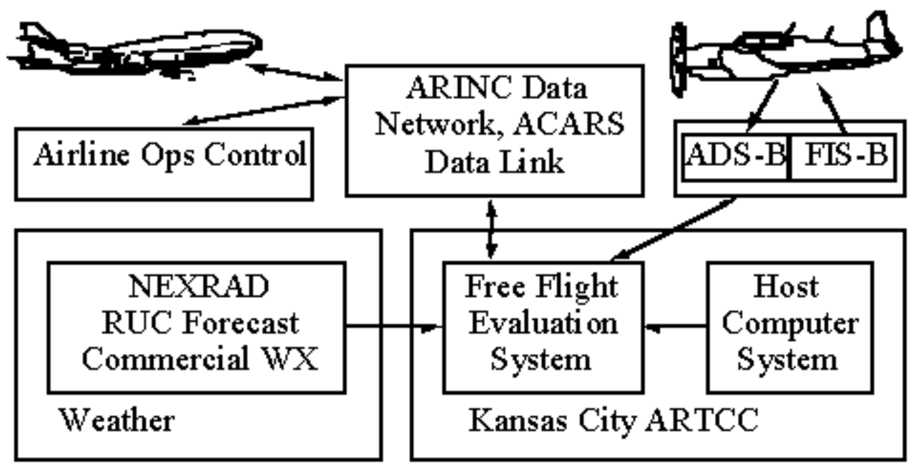

Figure 1. The Free Flight Evaluation System.

2.4 Research Scope

The purpose of this study is to examine in detail the effectiveness of using the above−described supplementary data sources to improve trajectory modeling. The emphasis of the study is on data sources that can be implemented in the near−term (next few years), and for which real, field−recorded data can be obtained for analysis. There are two parts to the study.

The first part relates to air−ground data link of aircraft state information via ACARS. ACARS reports have been collected in the field, using the FFES at ZKC. Airspeed, heading, and wind data are the items of primary interest. The characteristics of this data have been studied, algorithms have been implemented for using this data in trajectory modeling, and the impact of the data on trajectory modeling performance has been evaluated.

The second part relates to use of additional flight planning information from AOCs to improve modeling of aircraft performance. This part of the study is currently in progress, and will be the subject of a future report.

3. Trajectory Prediction

3.1Trajectory Modeling Overview

The FFES maintains a database of predicted trajectories for all aircraft for which a flight plan has been received from the HCS. These trajectories are used by a wide variety of prototype ATM DSS tools. The FFES/URET trajectory modeling algorithms use the data sources described above in combination with airspace adaptation data, a database of ATC procedural restrictions, and aircraft performance data to produce a predicted four−dimensional flight path. This flight path is expressed as a series of nodes. Flight between nodes is assumed to be in a straight line with linearly−varying speed and altitude. The trajectory modeling process is done in four major steps:

1. Lateral Modeling. Convert the flight plan to a list of latitude/longitude points ("route conversion"). Create an initial list of trajectory nodes. If the aircraft is not in conformance to the cleared route, apply heuristics and construct a return−to−route path. Break up long great circle segments into shorter straight segments. Add buffer segments around significant turns.
2. Airspace Restriction Application. Apply a set of airspace−specific rules to the route in order to generate altitude and speed constraints which match the standard ATC procedures in effect at this time.
3. Profile Modeling. Insert altitude and speed maneuvers into the route to reflect cleared altitudes and speeds, imposed ATC restrictions, and other limitations (final descent, the 250−knot speed limit, etc.). An iterative process is used to develop a flight profile that meets all of the restrictions. A table of aircraft performance characteristics is used in combination with observed performance to derive climb/descent rates and speeds.
4. Longitudinal (Along−Track) Calculations. Using node airspeeds and forecasted winds, calculate any groundspeeds that were not computed in the previous step, and compute estimated time of arrival (ETA) at all trajectory nodes.

The details of steps 1 through 3 of this process are lengthy and generally beyond the scope of this paper. Please contact the author if more information is desired. The longitudinal calculations are impacted the most by the downlinked airspeed and wind information, so they will be described further.

Predicting the future aircraft position along the route of flight is a straightforward process, but subject to many significant error sources. When a flight is first modeled, and there is no track data available, the process is as follows:

1. During the profile modeling process, an airspeed is assigned to all trajectory nodes. In climb and descent, this data is obtained from aircraft performance tables. In the cruise phase, the filed airspeed is used.
2. From the RUC forecast, winds and temperatures are assigned to all nodes.
3. Groundspeeds are computed at all nodes by completing the "wind triangle" produced by the airspeed and forecast winds.
4. ETAs are assigned to all nodes, assuming that groundspeed varies linearly between nodes.

This process is adaptively modified when track reports are available. When a trajectory needs to be recomputed, due either to a conformance violation or a flight plan change, the aircraft’s actual groundspeed is estimated by a smoothing filter applied to the recent track history. This result is used in combination with the forecasted winds to compute an airspeed estimate, which in turn is used to modify the nominal speeds used in the trajectory recomputation. This procedure has been shown to provide some improvement in longitudinal position predictions. However, the accuracy of the groundspeed estimate and the corresponding improvement in prediction accuracy are limited by noise in the radar track reports. A similar procedure is used to estimate actual climb and descent gradients, in order to improve vertical flight path modeling.

3.2 Trajectory Prediction Metrics

In order to determine whether additional data sources improve trajectory modeling, a series of prediction accuracy metrics were defined. The metrics address two primary features of predicted trajectories: prediction accuracy and stability.

Prediction Accuracy. Predicting aircraft trajectories in today's ATM system is a difficult problem. Prediction errors can come from many sources. Some examples:

5. Aircraft performance variations from the assumed nominal levels
6. Variations of pilot technique and navigational precision between aircraft
7. ATC vectors to avoid traffic or weather
8. Clearances which are given verbally but not entered into the ARTCC computer
9. ATC procedural restrictions

A prediction is made at a moment in time at which the current flight plan is assumed to be known, and if airborne, the current position, altitude, and speed of the aircraft is known. Errors can then be evaluated by comparing the track history of the aircraft with the corresponding (in time) point on the predicted trajectory. Errors are evaluated in the lateral (cross−track), vertical (altitude), and longitudinal (along−track) axes.

There are two ways to present this accuracy data. One way is to simply plot error growth as a function of time from when the trajectory is initially computed. This answers the question of overall predictability; given all the knowledge available to the system at a particular time, how well can the system predict the future position of the aircraft?

A second way to look at accuracy is to examine only those segments of the trajectory for which the flight plan is correctly known. For example, if a new clearance was given 10 minutes after the initial trajectory was computed, then errors will not be evaluated beyond that point. This approach answers the following question: If the system knows *fully* the flight plan of the aircraft, how well can it predict future positions?

Predictability metrics in this paper will be presented using the first of these metrics. In current practice, knowledge of the flight plan is rarely exact; as mentioned above, controllers often give certain clearances verbally without entering them into the automation. It is therefore difficult to restrict the error measurement to cases in which the flight plan is exactly known. Also, for the purposes of decision support tools which use the predicted trajectories, it is the first of these metrics which indicates how well the future position of the aircraft can really be predicted. This distinction is made here for two reasons: (1) the error magnitudes will appear quite large under certain conditions; this is often due to flight plan changes rather than algorithmic or data quality issues, and (2) the second metric is also commonly used by other researchers in this field.

Figure 2 is an example of trajectory prediction error as a function of time for all aircraft which were modeled in one of the time segments of interest. This plot includes all phases of flight, and is based on the standard modeling procedures in which ACARS reports are NOT used.

Lateral errors tend to grow rapidly at first, and then flatten out. A significant portion of the lateral prediction errors is most likely due to unknown clearances such as vector instructions or verbal "direct−to" instructions. Navigational errors also play a part; analysis has shown that prediction errors for aircraft with modern area navigation systems are lower than non−equipped aircraft.

The mean altitude errors grow rapidly due to errors in predicting the start point of altitude maneuvers, and difficulty in predicting accurate climb and descent rates. This is due to many factors. One of the most important ones is that flights are often subject to ATC procedural restrictions, which produce level−offs during climbs and "steps" in the descent. Determining these restrictions and when they are active is one of the most difficult parts of the modeling task (see Reference 2 for further details). An additional error source is the lack of specific performance data (takeoff weight, etc.) for individual flights.

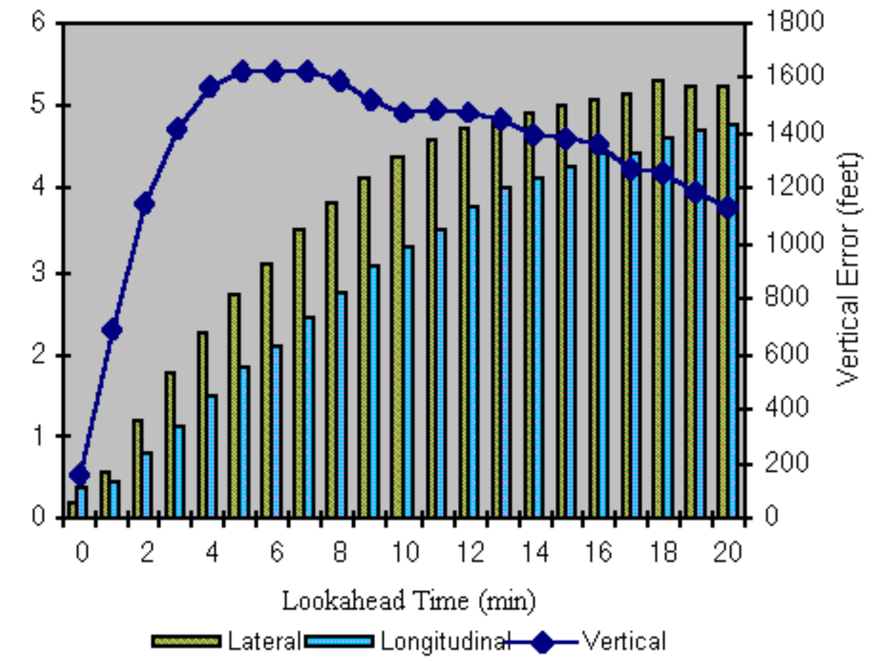

Figure 2. Mean Trajectory Prediction Error vs. Lookahead Time.
From a three−hour period including 353 flights, for which 3194 trajectories were modeled.

Longitudinal prediction error tends to grow with time in approximately linear fashion. These errors are mostly due to speed− and wind−related uncertainties. This report focuses primarily on this issue, since it can be addressed through air−ground data link reporting of speed and wind. It is of course equally important to reduce lateral and vertical prediction errors; other research at CAASD is addressing these issues.

Stability of Trajectories. Stability of predicted trajectories is important for functions which use trajectory data. A conflict alert which is based on constantly changing trajectories is likely to present variable and possibly contradictory information to a controller. In the URET and FFES systems, trajectories get recomputed for two main reasons. First, any change in flight plan information from the HCS requires the trajectory to be recomputed. This is a necessary and unavoidable function. Second, the system monitors the relationship of received track reports to the predicted trajectory, and when the difference exceeds a predetermined set of bounds, the trajectory is recomputed. This function is called "reconformance", and is necessary to ensure that conflict alert or any other system function is using a good set of data. In the URET system, for example, the baseline longitudinal reconformance bound is set at 1.5 nautical miles, and trajectories are recomputed whenever this bound is violated.

The most general measure of trajectory stability, therefore, is the frequency with which trajectory recomputations occur. A more specific stability measure of the trajectory prediction algorithm can be obtained by looking only at the frequency with which reconformance events occur, independent of flight plan changes. This latter metric will be used to compare trajectory predictions made with and without the use of air−ground data link reports.

4. Using Aircraft−Reported Speed and Wind

4.1 Air−Ground Data Characteristics

As noted above, this study was focussed on data available from current ACARS−based reporting systems. In particular, UPS, Delta Airlines, and United Airlines provided messages for the experiment. Message formats varied between airline and between airframe types, due to variations in avionics equipage. Generally, the aircraft automatically sent a periodic position report message which contained all or some of the following information: position, altitude, airspeed (Mach), groundspeed, heading, wind speed and direction, and temperature. A special message implemented for this project by UPS also included such items as vertical speed and estimated weight. The default reporting period varied between installations, ranging from 5 to 7 minutes between reports. However, UPS worked with CAASD on two occasions to decrease the reporting interval to 2 minutes, and to allow CAASD to uplink requests to certain specially−equipped aircraft to report every 30 seconds.

A limitation of the reports was the lack of universal clock synchronization. Typically, the timestamp on the messages varied according to the bias of the aircraft’s onboard clock. This offset, combined with the unknown ACARS message delivery latency, made the position information difficult to use. However, the primary interest in this study was speed and meteorological information, which is not as time−sensitive, so the time bias is not likely to have significantly affected the results presented below.

4.2 Integrating Data Link Reports into Trajectory Prediction

A simple form of data fusion was used to integrate the ACARS position reports and HCS track reports into an improved estimate of aircraft state. The position and altitude data are taken from the HCS radar report, since they are updated every 12 seconds. If groundspeed and heading are explicitly available from the ACARS report, they replace the HCS tracker data. If airspeed, heading, and winds are available from the ACARS report, the groundspeed is derived and used to replace the HCS data. Also, airspeed, heading, winds, and temperature are stored in the aircraft track record as auxiliary information.

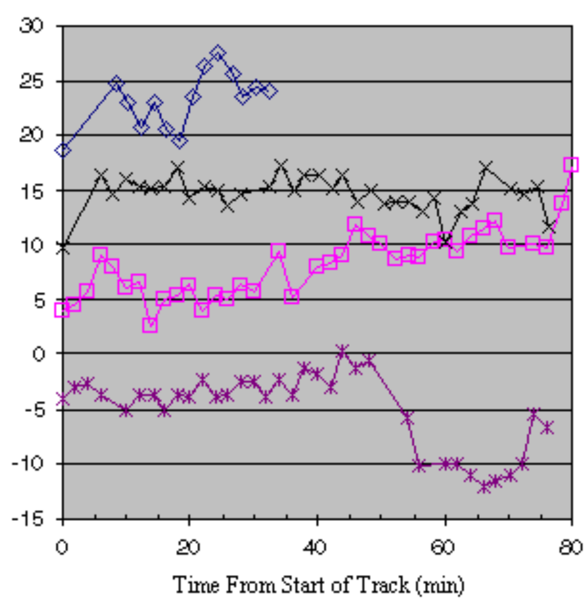

Figure 3. Sample Measured Airspeed Histories
Each trace represents the cruise phase of one flight.
The difference between ACARS−reported airspeed and flight plan (filed) airspeed is plotted against time.

When trajectories are built for one of these "blended targets," all available information is used. If the local wind and temperature conditions were reported via ACARS, these are used instead of the forecasted values for the current aircraft location. If airspeed is available, it is used directly instead of deriving an airspeed from the HCS−reported groundspeed and forecasted winds. In this way, wind forecast errors and speed errors introduced from the HCS radar tracker can be attenuated. The results presented below compare trajectory prediction metrics between cases in which the ACARS data was used (the "blended" case) and those, for the same aircraft, for which the ACARS data was not used.

An additional component of the study involved using the wind and temperature data to update the forecast. Although the RUC product does include ACARS reporting data, it is between 3 and 6 hours old. In principle, modifying the forecast with the latest measurements should provide accuracy improvements not only when predicting trajectories for the reporting aircraft, but for all other aircraft traversing the airspace for which recent ACARS reports have been received.

4.3 Data Collection

In order to test this "data blending" technique, the FFES was used to collect HCS, ACARS, and RUC data at selected periods. Overall, several months of data were collected. From this large data set, a series of particularly interesting segments were chosen. A typical analysis segment lasted between 3 and 4 hours, contained between 15 and 30 reporting aircraft, and included between 400 and 750 total ACARS reports. ARINC provided invaluable support to this effort by waiving the ACARS transmission costs for the messages received in the study.

5. Analysis of Airspeed and Wind Variation

5.1 Observed Airspeed and Wind Variations

The two primary sources of error in the longitudinal prediction computation are imperfectly known airspeed and winds. For example, although a pilot or autopilot will normally fly the aircraft at a single target airspeed for most of the cruise phase, this airspeed may not exactly correspond to the filed airspeed. In addition, there will be relatively small variations of the actual airspeed around the target. Figure 3 illustrates a typical set of airspeed traces, in which the difference between the ACARS−reported and filed airspeeds are plotted vs. track time.

Similarly, the wind forecast is likely to introduce two types of errors. One is a general bias error, in which the general magnitude or direction of the wind over a region will be slightly different from the actual winds. The other type is due to shorter scale wind variations, which are not captured by the forecast grid. Figure 4 is a scatterplot of the difference between measured and forecasted wind speeds at three cruise altitudes, for a two hour period during which 7 reporting aircraft crossed ZKC traveling approximately eastbound. The prevailing winds at altitude were westerly during this time period, with a maximum speed of approximately 100 knots, and the forecast varied only slightly with latitude across ZKC.

Despite the data scatter, it is apparent that the difference between the forecast and the actual (as measured) winds is dependent on location. At the western end of the center, the wind speed forecast was approximately 10 knots too high. As the aircraft proceeded eastward, the measured winds became slightly greater than the forecast winds, with some shorter scale variation around 90°W. Similar results were seen with other data segments. This geographically−localized error suggests that updating the forecasted winds used by the trajectory modeler with ACARS reports could reduce prediction errors.

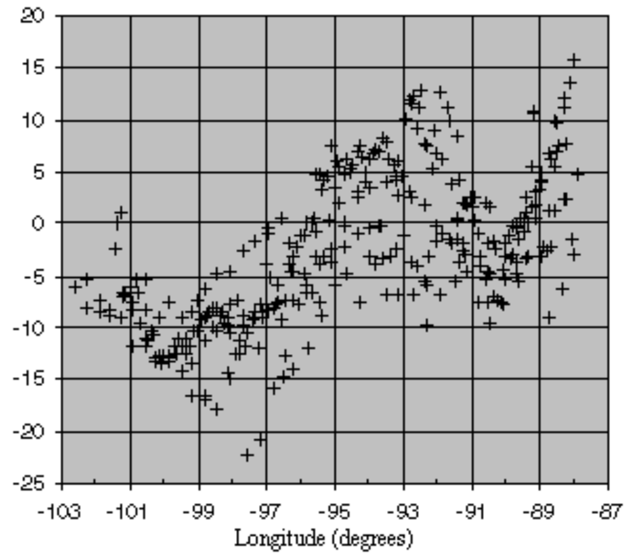

Figure 4. Measured vs. Forecasted Wind Speed.
From reports of 7 aircraft at FL370 over two hours,
the difference between the measured and forecasted wind speed
is plotted against longitude of the report position.

Longitudinal prediction error is affected by the component of the wind variations which lies along the aircraft flight path. Figure 5 shows traces of along−track wind differences between reported and forecast values for three aircraft, which took slightly different routes through the same data set used in Figure 4.

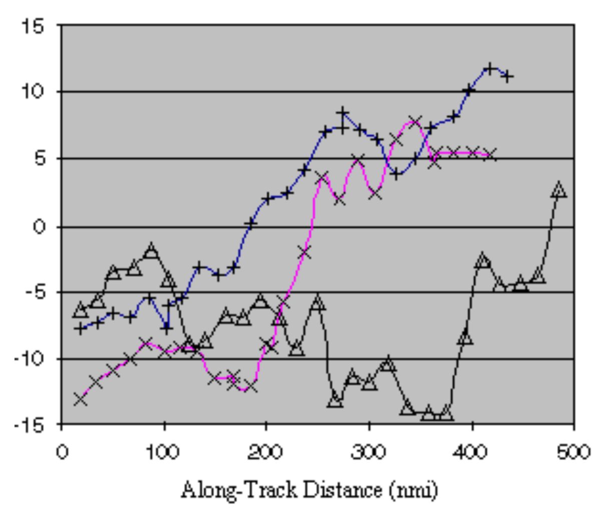

Figure 5. Measured vs. Forecasted Winds Along Aircraft Track
Wind differences are projected along the aircraft track
and plotted against distance along the track.

5.2 Impact on Trajectory Prediction

All of these variations manifest themselves as errors in the predicted groundspeed. Since groundspeed is integrated over time to predict future aircraft position, even small errors in groundspeed will eventually add up to produce relatively large position errors. A statistical model of these airspeed and wind variations would be a useful tool for evaluating the impact of these variations on predicted trajectories. Therefore, the following model was developed, based on analysis of the ACARS reporting data.

The along−track position of an aircraft from an initial point can be expressed as the integral of the groundspeed, composed of the sum of the airspeed and along−track wind:

$$X_{actual} = \int \left(V_a + W_u\right) dt \quad (1)$$

where V_a is the aircraft airspeed and W_u is the tailwind−positive wind component along the aircraft track. This assumes that the heading and ground track angle of the aircraft are the same, i.e. there is no significant crosswind. Since the airspeed and wind variations will have the largest effect on the prediction error when the wind direction is aligned with the aircraft track, this is a reasonable and conservative simplification.

Since only flight plan information and the wind forecast are initially available to the modeler, the aircraft is nominally assumed to be flying at the filed airspeed with the forecast winds. The predicted along−track position is then:

$$X_{predicted} = \int \left(V_{a,\ filed} + W_{u,\ forecast}\right) dt \quad (2)$$

Expressing the airspeed and along−track winds as the nominal value plus a variation results in

$$V_a = V_{a,\ filed} + v \qquad W_u = W_{u,\ forecast} + w \quad (3)$$

The prediction error, x, can then be expressed as

$$x = X_{actual} - X_{predicted} = \int \left(v + w\right) dt \quad (4)$$

It is apparent from the reported airspeed and wind data that variations occur on a number of time and space scales, which complicates modeling of the variations. In the practical application (in URET) of computed trajectories to conflict detection, a prediction time horizon of 20 minutes is used. At a typical cruise speed of 450 knots, this is equivalent to 150 nmi. If the timeframe of interest is limited to 20 minutes in the future, the variation model can be simplified. Figure 2 suggests that the difference between the actual and filed airspeed over this time period can be modeled as the sum of a constant bias and a time−dependent term:

$$v(t) = a_v + b_v(t) \quad (5)$$

where a_v is assumed to be a random variable of unknown distribution and b_v is a random process with a zero expected value and a to−be−determined autocorrelation function. For now, assume a similar form for the along−track wind variation from the forecast (although Figure 4 suggests that this may be too simple). Also, assume that the along−track wind variation and the airspeed variations are statistically independent. Then, over this relatively short time−frame, the error at a time τ seconds from the prediction will be:

$$x(\tau) = \int_0^{\tau} \left(a_v + b_v(t) + a_u + b_u(t)\right) dt \quad (6)$$

$$x(\tau) = a_v\tau + a_u\tau + \int_0^\tau \left(b_v(t) + b_u(t)\right)dt \qquad (7)$$

This expression represents the error due to a particular time history of airspeed and wind variation. Statistically, it is of interest to look at a overall measure of error growth. The trajectory prediction errors which will be presented later are in the form of average absolute error as a function of time. Since the error is a random process, this corresponds to the *expected value of the absolute value* of $x(\tau)$:

$$E\left|x(\tau)\right| = E\left|a_v\right|\tau + E\left|a_u\right|\tau + E\left|\int_0^\tau \left(b_v(t) + b_u(t)\right)dt\right| \qquad (8)$$

Figure 2 suggests, for the case of airspeed variation over a 20 minute interval, that the bias term a_v will have a stronger effect on error growth than the zero−mean random process b_v. This is borne out by similar plots from the other data segments. Therefore, the initial effort was aimed at modeling this bias term. Airspeed variations were averaged for each reporting flight over several days of recording, and the distribution across flights was examined. Analysis indicated that the bias is approximated well by a zero−mean, normal distribution with a standard deviation of 11.8 knots.

A slightly different strategy was taken to analyze the difference between measured (assumed to be actual) and forecasted along−track winds. Data were taken from several days during which a 2 minute reporting interval was used. These measurements were combined, and the result was also approximated well by a zero−mean, normal distribution. Standard deviation was 9.4 knots.

In the case of a zero−mean, normal distribution for a_v and a_u, the first two terms on the right side of equation 8 can be evaluated in closed form. The expected value of the absolute error for such a variable is found by choosing the 0.75 point on the cumulative normal probability distribution, which works out to:

$$E\left|a\right| = 0.674\,\sigma_a \qquad (9)$$

Applying this to Equation 8, the bias terms taken together indicate a longitudinal growth rate of 0.24 nautical miles per minute of lookahead time. The airspeed variation and wind variation effect are of similar magnitude. As illustrated by Figure 2, longitudinal prediction error does tend to grow in roughly linear fashion, and the error rate on that plot is not far from the error growth rate computed here. However, the trajectory modeling algorithms attempt to adapt to the observed groundspeed whenever a reconformance is required, which would compensate for some of the bias term error.

On the other hand, additional error will accrue due to the random process terms in equation 8. Plotting the airspeed data as in Figure 3 indicates that the shorter−scale airspeed variations are unlikely to add much to prediction error, since they tend to be significantly faster than the 20 minute timescale, with the exception of occasional "step changes" in the airspeed. This is true to a lesser extent with the along−track wind variations, which tend to vary slower with time and distance and thus would be expected to contribute a non−negligible component to the error.

For this reason, additional work is underway to study the impact of this component of the wind variation. A random process model will be fitted to the data using spectral analysis techniques, and the contribution to longitudinal prediction error will be evaluated.

The important point is that the airspeed and wind bias terms contribute significantly to longitudinal prediction error, and that this source of error would likely be reduced by the availability of better airspeed and wind data, such as that provided by the ACARS data link reports.

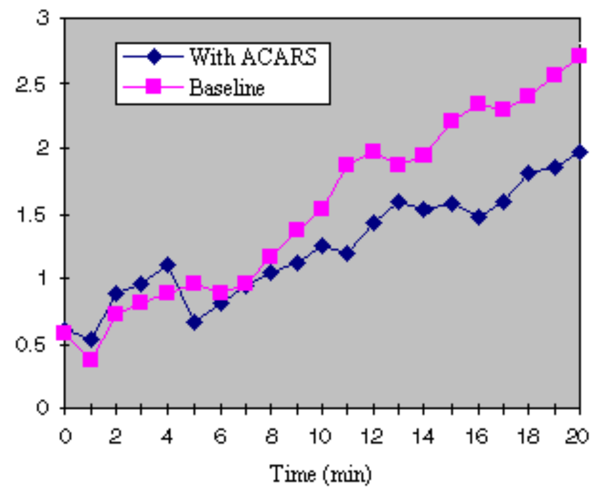

Figure 6. ACARS Reporting Impact on Longitudinal Prediction Error Growth.
Mean longitudinal prediction errors as a function of lookahead time are shown for 14 ACARS−reporting flights during the cruise phase, modeled with and without the ACARS−reported data.

6. Trajectory Prediction Results

In order to evaluate the effect of the data link reports on trajectory modeling, HCS, RUC, and ACARS data from the time segments of interest were replayed through the FFES algorithms both with and without data blending. In some of the runs, the ACARS reported wind and temperature data was used to update the forecast grid as well. The metrics described in Section 3.2 were used to quantify trajectory prediction performance differences.

6.1 Impact on Prediction Error

Adding the ACARS reports to the trajectory modeling process was expected to increase longitudinal prediction accuracy, because the reports provided better knowledge of the aircraft airspeed and local wind conditions at the time of trajectory computation. Figure 6 shows the mean cruise−phase longitudinal prediction error for one data segment as a function of time. Aside from the variation at short lookahead times, the prediction error for flights modeled using ACARS reports clearly grow slower with time.

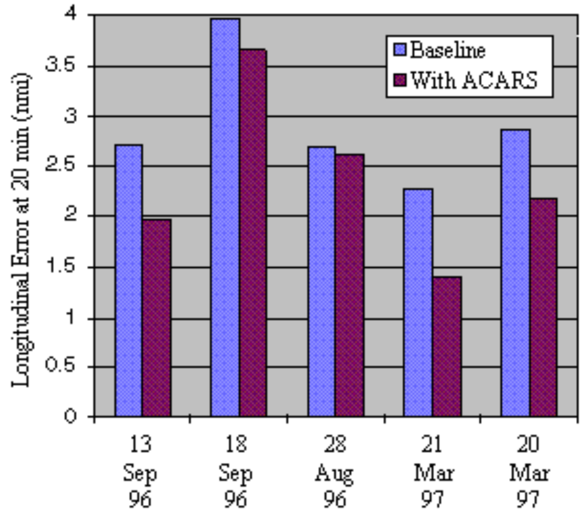

Figure 7. ACARS Reporting Impact on Longitudinal Prediction Error.
This plot summarizes the level−flight longitudinal prediction error at 20 minutes lookahead for 5 data segments.

This effect was seen in all of the data segments studied [Figure 7]. Even though overall size of the mean longitudinal error changed due to the different characteristics of the data segments (different wind patterns, different aircraft density, etc.) the ACARS−aided flights always exhibited smaller longitudinal prediction error growth than when those same flights were modeled without ACARS reports.

This data indicates that using the ACARS reports reduced the mean longitudinal error at the 20 minute mark by between 0.25 and 1.0 miles. Assuming a linear growth pattern for the longitudinal error, this indicates a reduction of 0.013 to 0.050 nautical miles per minute in growth rate. The average 20 minute error without ACARS reporting ranged from 2.3 to 4 nmi, corresponding to a growth rate between 0.12 and 0.20 nmi/min.

		No. of Reconformances		
Data Segment	No. of Aircraft	Baseline	With ACARS	Change
28 Aug 96: 0300−0600 UTC	13	155	130	−16%
29 Aug 96: 0300−0630 UTC	11	124	109	−12%
13 Sept 96: 0300−0630 UTC	14	222	187	−16%
18 Dec 96: 2000−2300 UTC	17	145	135	−7%

6.2 Impact on Trajectory Stability

In order to evaluate the impact of the ACARS reports on trajectory stability, the reconformance frequency for ACARS−reporting flights was examined. The flights were modeled with and without using the ACARS data, the portion of the flight for which ACARS data was not available was discarded (generally a few minutes at the beginning of the radar track), and the number of reconformances required was counted. The results for 4 data segments are presented in Table 1.

The table shows that the total number of reconformances decreased when ACARS reports were used, indicating that the resulting trajectories were more stable than when the reports were not used. The overall difference across the four data segments was 14%, which was found to be highly statistically significant ($\alpha < 0.01$) using a paired t−test.

6.3 Updating the Wind Forecast

A series of trajectory prediction runs were also done in which ACARS−reported winds were used to update the wind forecast. A simple approach was used; when an ACARS wind report was received, the reported wind speed and direction was used to replace the forecasted value at the nearest node in the forecast grid. If no reports for a given node were received for an hour, then the winds at that node reverted to the forecasted value.

The results of these runs were inconclusive. Although analysis of the difference between the measured and forecasted winds indicates that this type of updating has potential to be useful, it appeared that there were not reporting aircraft to affect significant numbers of the forecast grid nodes.

7. Conclusions

The use of aircraft speed and wind reports to reduce trajectory prediction errors in an ATM decision support system has been evaluated. Aircraft reports were collected over a period of months via ACARS data link. Analysis indicates that airspeed and wind variability can contribute significantly to aircraft trajectory prediction errors, and a model was developed to estimate the magnitude of the errors.

A simple form of data fusion was used to incorporate aircraft reports into a prototype ATM trajectory prediction algorithm, in order to help compensate for this variability. The aircraft reports were found to improve trajectory along−track prediction error by an average of 10% to 15%. Trajectory stability was also improved, in that the number of trajectory recomputations required to maintain consistency between reported and predicted data was reduced.

An important consequence of this finding is that these results were achieved using relatively infrequent reporting (typically with 2 to 5 minute reporting intervals), which implies that a high−bandwidth data link is not required to implement this technique.

Therefore, should a DSS application be proposed that requires (or could benefit from) additional trajectory prediction accuracy, incorporation of aircraft reporting via data link is a viable near−term option, subject to the outcome of an appropriate cost−benefit analysis.

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