# WIND PREDICTION ACCURACY FOR AIR TRAFFIC MANAGEMENT DECISION SUPPORT TOOLS*†

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## ABSTRACT

Air traffic automation depends on accurate trajectory predictions. Flight tests show that wind errors are a large source of error. Wind-field accuracy is sufficient on average, but large errors occasionally exist that cause significant errors in trajectory-prediction. A year long study was conducted to better understand the wind-prediction errors, to establish metrics for quantifying large errors, and to validate two approaches to improve wind prediction accuracy.

Three methods are discussed for quantifying large errors: percentage of point errors that exceed 10 m/s, probability distribution of point errors, and the number of hourly time periods with a high number of large errors.

The baseline wind-prediction system evaluated for this study is the Rapid Update Cycle (RUC). Two approaches to improving the original RUC wind predictions are examined. The first approach is to enhance RUC in terms of increased model resolution, enhancement of the model physics, and increased observational input data. The second method is to augment the RUC output, in near-real time, through an optimal-interpolation scheme that incorporates the latest aircraft reports received since the last RUC update. Both approaches are shown to greatly reduce the occurrence of large wind errors.

## 1. SUMMARY

Air Traffic Management (ATM) Decision Support Tools (DST) depend on accurate trajectory predictions to provide controllers with operationally acceptable advisories. Flight tests in 1992 and 1994 have shown that wind-prediction errors may be the largest source of trajectory-prediction error. Although wind-field prediction accuracy may be sufficient on average, these flight tests revealed large errors that occasionally exist over large enough regions of airspace and time to cause significant errors in trajectory-prediction accuracy. Such errors, even if they only occur for short periods, a few times a year, may significantly diminish the operational acceptance of ATM DST advisories. A year long study of the Denver Center airspace was conducted to better understand the magnitude and source of wind-prediction errors, to establish metrics for quantifying large errors that may be critical to ATM decision support, and to validate two approaches to improve wind prediction accuracy, particularly with respect to errors significant to ATM automation.

Three methods are discussed for measuring large errors given spot checks of wind accuracy. The first, large point error percentage, indicates the percentage of point wind-vector errors (within a sample) that exceed 10 m/s. The value 10 m/s is taken as a threshold at which wind errors become problematic from an ATM-DST perspective. The second, error probability distribution, looks at the distribution of point wind-vector errors. This metric offers greater flexibility in that no a priori threshold is applied. While large point errors indicate a problem with a wind forecast, a single large point error does not lead to a poor trajectory prediction. The third method, large hourly error percentage, determines the number of hourly time periods within which a certain percentage of exceed a threshold, for example 10 m/s. The advantage of this metric is its applicability to determining the frequency of periods within which ATM DSTs may be negatively impacted by groups of large point errors.

The baseline wind-prediction system evaluated for this study was the Rapid Update Cycle (RUC). Two approaches to improve the original RUC wind

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† Opinions, interpretations, conclusions, and recommendations are those of the author and are not necessarily endorsed by the United States Air Force. Corresponding author address: Rodney E. Cole, Massachusetts Institute of Technology, Lincoln Laboratory, 244 Wood Street, Lexington, Massachusetts 02420-9185; e-mail: rodc@ll.mit.edu

predictions were examined. The first approach was to enhance RUC in terms of increased model resolution, enhancement of the model physics, and increased observational input data. The second method is to augment the RUC output, in near real time, through an optimal-interpolation scheme that incorporates the latest aircraft reports receive since the last RUC update. Both approaches are shown to greatly reduce the occurrence of large wind errors. For example, the improvement in the RUC model reduced the percentage of point errors greater than 10 m/s from 8% to 3%, and the augmentation of RUC reduced such errors from 11% to 4% (using a slightly different set of RUC forecasts.)

## 2. INTRODUCTION

The performance of Air Traffic Management (ATM) flight deck decision support (DST) tools depends in large part on the accuracy of the supporting 4D trajectory predictions. This is particularly relevant to conflict prediction and active advisories that suggest clearances for the resolution of conflicts and the conformance with traffic-flow management flow-rate constraints (e.g., arrival metering / required time of arrival). Flight test results have indicated that wind prediction errors may represent the largest source of trajectory prediction error (Williams and Green, 1998; Jardin and Green, 1998). The tests also discovered relatively large errors (e.g., greater than 20 knots), existing in pockets of space and time critical to ATM DST performance (one or more sectors, greater than 20 minutes). Classic RMS aggregate prediction-accuracy statistics most often used in past studies inadequately represent these operationally significant errors.

To facilitate the identification and reduction of DST-critical wind prediction errors, NASA is leading a collaborative research and development activity with MIT Lincoln Laboratory and the Forecast Systems Lab of the National Oceanographic and Atmospheric Administration (NOAA). This activity, begun in 1996, is focussed on the development of key wind error metrics for ATM DST performance, assessment of wind prediction skill for state of the art systems, and development/validation of system enhancements to improve skill. A yearlong study was conducted for the Denver Center airspace in 1996-1997.

Two complementary wind prediction systems were analyzed and compared to the forecast performance of the "then standard" 60 km Rapid Update Cycle - version 1 (RUC-1) a mesoscale numerical weather prediction model (Schwartz and Benjamin, 1998). The first system, developed by NOAA, was the prototype 40-km RUC-2 that became operational at NCEP in 1999. The RUC is a regional numerical weather prediction and data assimilation system that runs at the National Centers for Environmental Prediction (NCEP) to provide high-frequency, 3D analyses and short-range (out to 12 h) forecasts.

The RUC differs from other forecast models run at NCEP in that it runs at a higher frequency, with RUC-1 run every three hours producing a set of hourly forecasts and with RUC-2 run hourly producing a set of hourly forecasts. In addition to a finer resolution grid, RUC-2 uses more sophisticated physics than the RUC-1, and additional observation sources. The high-frequency atmospheric observations which allow this rapid updating include those from commercial aircraft equipped with Aircraft Communication Addressing and Reporting System (ACARS), wind profiles from various kinds of vertically pointing radars, surface observations, and estimates of moisture and winds from satellites. The RUC horizontal domain covers the 48 lower United States and adjacent parts of Canada, Mexico, and oceanic areas. The initial operational version of the RUC was implemented at NCEP in September 1994 with a 60- km horizontal resolution. A major upgrade was implemented in April 1999 as the 40-km RUC-2.

The second system studied, Augmented Winds (AW), is a prototype en route wind application developed by MIT LL based on the Terminal Winds analysis (Cole, et al., 2000) developed for the FAA's Integrated Terminal Wind System (ITWS) (Evans and Ducot, 1994). AW would run at a local facility (Center) level. The Terminal Winds is a data assimilation system that uses RUC wind forecasts and recent local measurements of the wind to produce wind nowcasts. These local measurements can come from surface observing systems, FAA and NWS Doppler weather radars, and ACARS. The ITWS TW system produces two wind fields: one with a horizontal resolution of 10 km and a 30 minute update rate and one with a horizontal resolution of 2 km that updates every five minutes. The 2 km resolution grid is nested within the 10 km resolution grid. The algorithm starts with an initial estimate and modifies it to agree with the observations in a general least-squares sense via the Gauss-Markov Theorem (Luenbuger, 1969). This scheme is closely related to traditional Optimal Interpolation and variational techniques (Daley, 1991). The AW analysis consists of only the 10 km analysis fed RUC-1 on the hour, and near real-time ACARS wind reports. Due to the RUC-1 3-hour run cycle and model run time, the 3-5 hour RUC-1 forecasts are used.

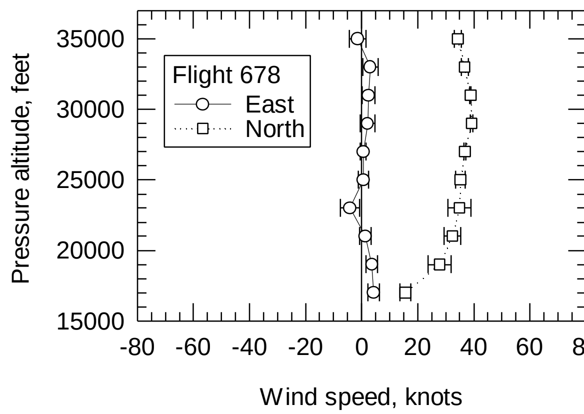
## 3. FLIGHT TEST RESULTS USING RUC-1

As part of an overall NASA effort to research and develop integrated user (FMS) and ATM (CTAS) systems (Denery and Erzberger, 1995), a series of flight tests were conducted at the Denver Center in 1992 (phase I) and 1994 (phase II). These tests were conducted to validate airborne and ground-based (ATM/CTAS) trajectory prediction accuracy, identify and measure major sources of trajectory prediction error, and explore procedures for the integration of FMS and CTAS decision support tools for arrival traffic (Williams and Green, 1998, and reference ATM-2000 abstract 84). A key finding of those tests was that wind prediction error was the greatest source of error for trajectory predictions on the order of 20 minutes time horizon (critical to ATM DST advisories for conflict prediction/resolution and conformance to flow-rate/metering constraints).

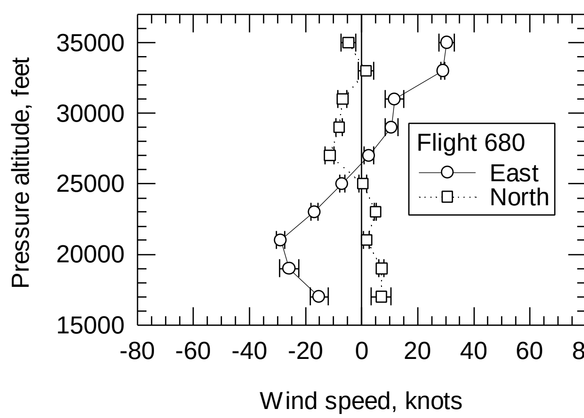
Phase I involved 24 test runs conducted over five flights over five days. The phase II test involved 26 test runs conducted over five flights over seven days. Each test run involved a 100-200 n.mi. arrival path including a cruise segment (FL350 or 330) followed by a descent segment (to 17,000 or 18,000 ft) to the Denver terminal area. The phase I test involved arrival runs from the northeast standard arrival route (arrival course of 237 degrees true), while the phase II test involved arrival runs along the northwest standard arrival route (initial course of 090 degrees true followed by a turn to 145 degrees true approximately 30 n.mi. prior to the end of the test run at the terminal-area boundary). Typical test flights included 5 runs over approximately 3 hours.

Wind prediction errors were measured, recorded, and analyzed in the following way. CTAS, the ATM DST ground system used at the Denver Center, received 3-hr updated forecasts of winds aloft from the MAPS (the RUC-1 prototype system) operated out of NOAA (Boulder CO). CTAS converted the MAPS data into local Denver-Center system coordinates and interpolated the data to determine the predicted winds aloft along a CTAS-predicted flight path. These CTAS-interpolated winds aloft along the path were recorded for each test run. The actual winds were measured and recorded (once per second with smoothing) on board NASA's Transport Systems Research Vehicle (TSRV) B737 test airplane using GPS for inertial velocity and the flight-test air data system for air-mass velocity. The wind speed errors were analyzed along each test-run's path.

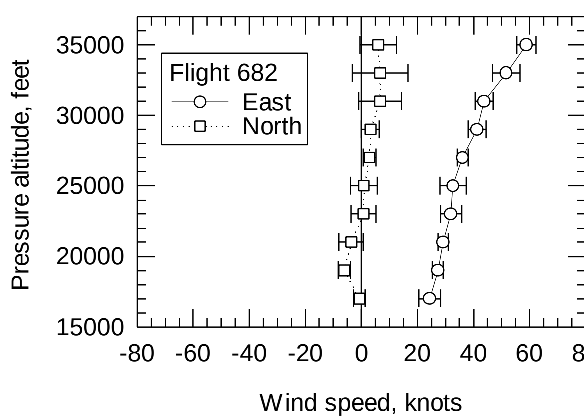
The measured winds of sample phase I and phase II flights are presented in figures 1 and 2, respectively. The winds along path are presented in terms of component speeds (knots) in the true north and east directions. For consistency between runs, the data are presented as a function of pressure altitude, with samples at discrete levels. Data from the multiple runs of each flight are combined into a mean and standard deviation of wind speed at that altitude. Data for the cruise altitude include all samples taken at cruise during the run whereas data for lower altitudes include a single sample for each run as the flight passed through that altitude. Figures 1 and 2 illustrate a relatively large variation in the winds aloft between flights with some variation within a flight (across multiple runs).




*(a) Flight 678*

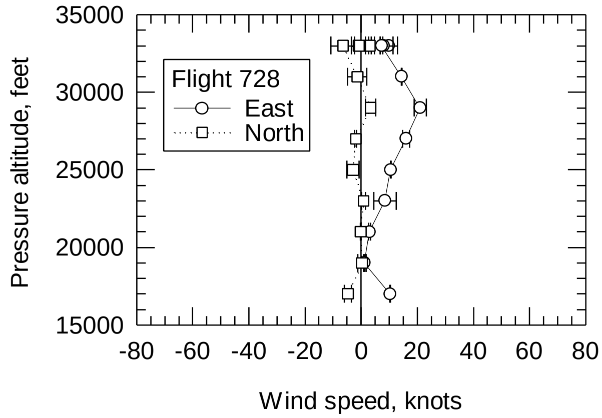



*(b) Flight 680*

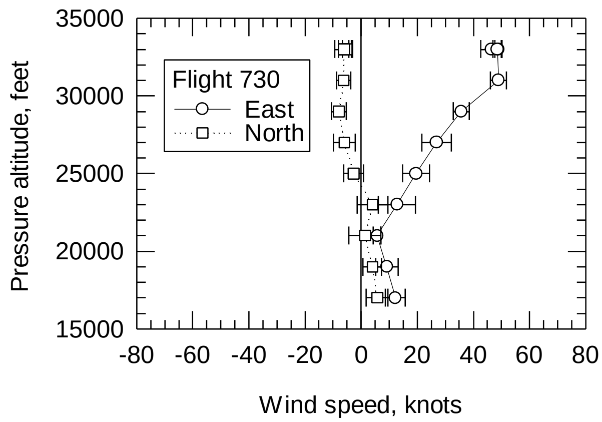



*(c) Flight 682*

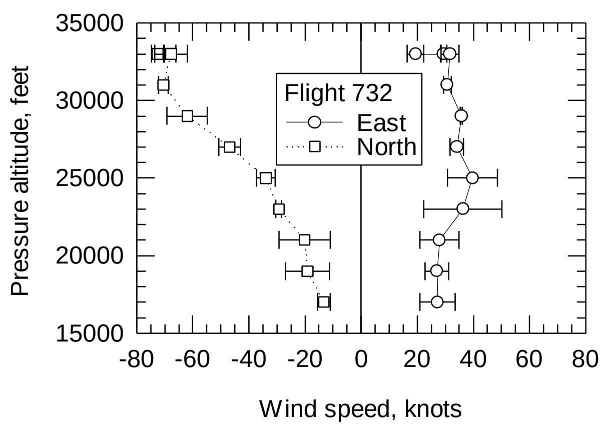
*Figure 1. Measured winds from the phase I test.*




*(a) Flight 728*



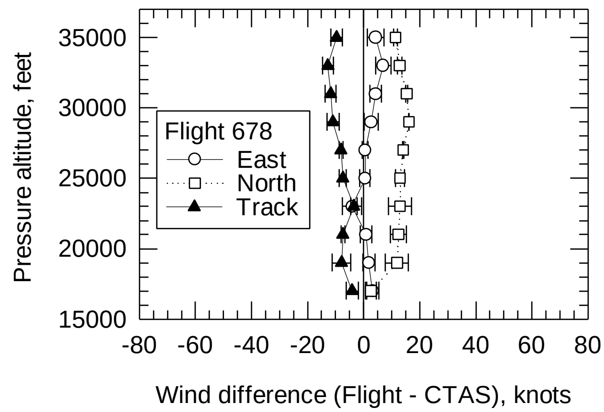

*(b) Flight 730*



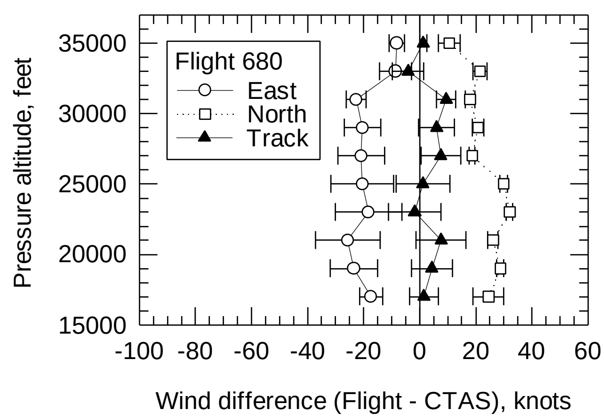

*(c) Flight 732*

*Figure 2. Measured winds from the phase II test.*

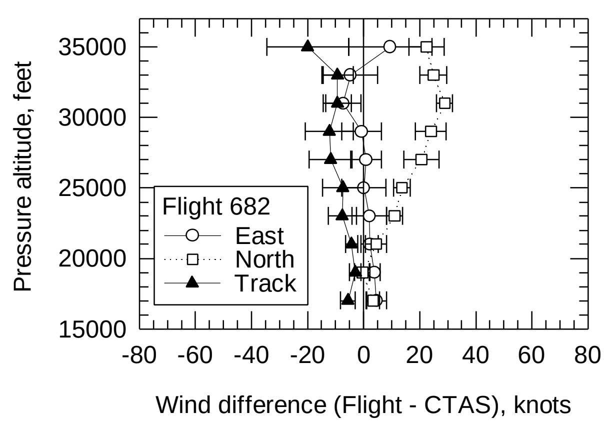
The measured/analyzed wind prediction errors are presented in figures 3 and 4, for phase I/II, respectively, using a similar format. Figure 5 presents a composite of the wind errors (mean and standard deviation) over all runs for each phase. Figures 3 and 4 indicate a fair amount of variation in mean wind error from one flight to another, with small variation across the test runs within a flight, as well as variation with altitude. In many cases, the errors exceed 20 knots, particularly in cruise where the error will accumulate over the time




*(a) Flight 678*

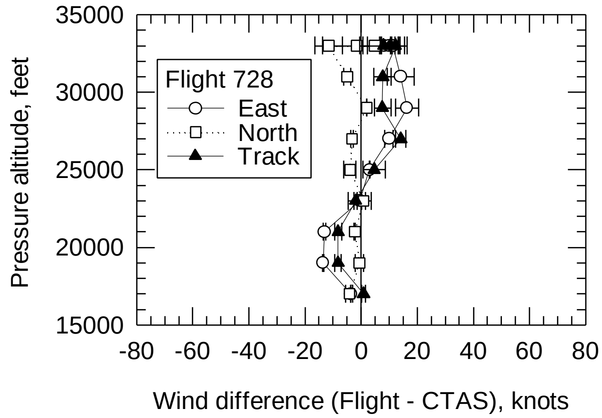



*(b) Flight 680*

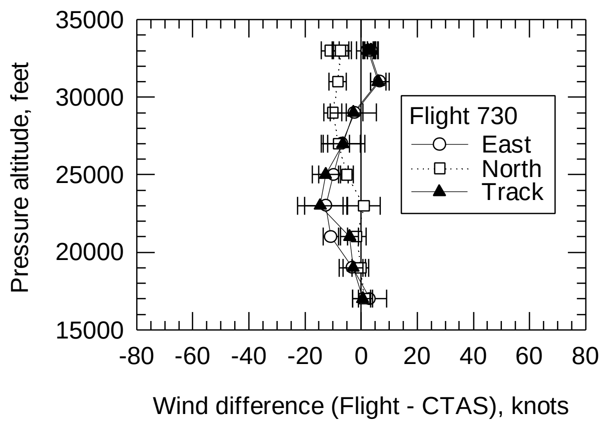



*(c) Flight 682*

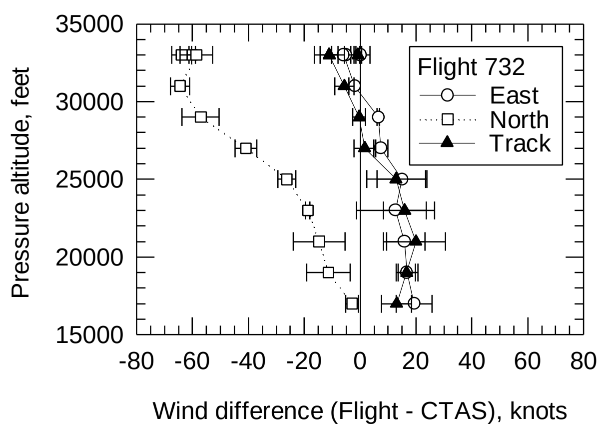
*Figure 3. CTAS wind model errors from the phase I test.*




*(a) Flight 728*




*(b) Flight 730*

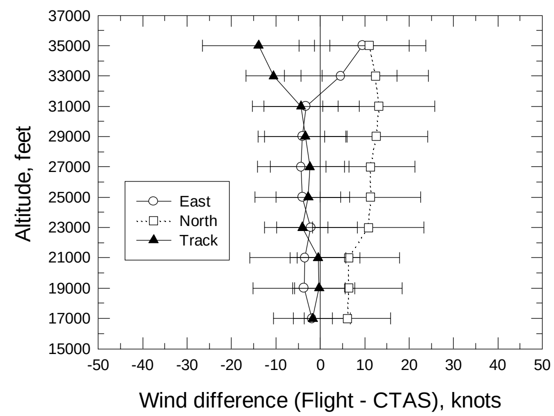



*(c) Flight 732*

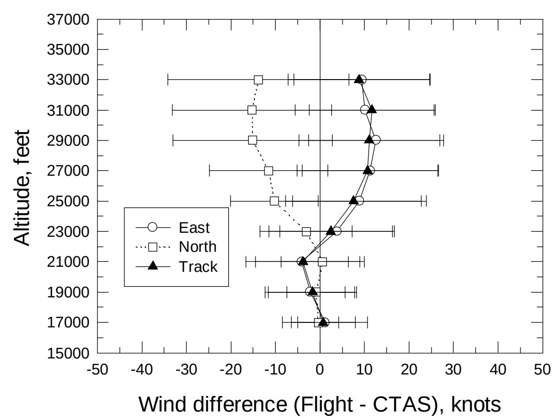
*Figure 4. CTAS wind model errors from the phase II test.*

horizon of a typical trajectory prediction. In particular, the test runs within flight 732 (phase II) consistently experienced cruise wind errors on the order of 60+ knots. This was attributed to a frontal passage in the general area that was incorrectly forecasted.

These flight test results reveal the existence of "large" wind prediction errors that may be detrimental to the performance of an ATM DST. Although these errors typically occur in scales of space and time that are critical to the performance of an ATM DST, they have little effect on classic wind prediction skill metrics such as aggregate RMS error computed over large spatial and temporal intervals.




*(a) phase I test*




*(b) phase II test*

*Figure 5. Composite CTAS wind model errors.*

## 4. METRICS FOR LARGE ERRORS

For ATM-tool applications, typically involving time horizons of 20-40 minutes, trajectory prediction errors in excess of 20-30 seconds may be disruptive and decrease the efficiency of ATM service (Green and Vivona 1996, Paielli and Erzberger 1996). In defining a metric for peak errors, it is useful to consider that the FAA standard for en-route radar-separation is 5 n.mi. under Instrument Flight Rules. A 15 kt (~7.7 m/s) mean error in along-track head wind component, over a 20-minute trajectory prediction, will result in a 5 n.mi. error in predicted position. For conflict prediction, trajectories are along different directions, and two trajectories will have different prediction errors. In the worst case of aircraft converging from opposite directions, the errors will be of opposite sign and much smaller mean along track errors may lead to poor ATM DST performance.

While headwind error is the most appropriate wind error to study if examining time-to-fly (TTF) errors for a given aircraft, it is easier to examine the magnitude of the vector error as this is independent of any knowledge of specific trajectories. Given a wind vector error, an aircraft flying perpendicular to the error vector will experience no headwind error. An aircraft flying parallel to the error vector will experience a headwind error equal to the magnitude of the error vector. Averaged over all directions, the mean headwind error will be the magnitude of the error vector times $2/\pi$ Thus a 15 kt headwind error is roughly equivalent to a 20 kt (~10m/s) vector error.

An ATM DST that provides active advisories (i.e., specific clearance suggestions for conflict resolution and flow-rate conformance), must provide high quality advisories at nearly all times. Even the occasional occurrence of incorrect advisories may not be operationally acceptable to controllers using the DST.

Standard measures of wind prediction accuracy are averaged over large periods of time and airspace. Alone, such aggregate metrics are not enough to determine the suitability of a wind-field prediction for for use by an active ATM DST. Most wind prediction systems provide adequate on-average performance since most of the time, over most of the airspace, the wind is only slowly varying and thus is easy to predict. However, as shown in the flight tests, unacceptably "large" wind errors (i.e., errors greater than 10 m/s) may exist over smaller periods of time and regions of airspace than have been typically studied in the meteorological literature. These large errors, potentially unacceptable for active ATM DST operations, are simply drowned out in the classical aggregate statistics typically used to assess the skill of wind-prediction systems.

Three types of metrics are introduced in this study to capture and quantify large errors. The simplest metric, large point error percentage, simply quantifies the percentage of wind vector errors larger than some value, for example 10 m/s. A second type of metric is to compute percentile values of the magnitude of wind vector errors. These percentile values give a probability distribution. The probability distribution has the advantage that no threshold is set in advance, each user of the data can choose their own threshold. While large point errors, for example caused by strong small-scale winds, will have little effect on time-to-fly estimates, the reduction in large point errors is a useful measure of improvement of wind prediction skill relative to ATM DST use.

A third type of metric, large hourly error percentage, is more directly related to ATM DST performance. This metric is based on the frequency of occurrence of large errors in temporal and spatial domains of interest to ATM automation, rather than the frequency of large point errors. While a large point error by itself will not cause a problem, a collection of such errors along a flight path will. The data are not dense enough in general to look at errors along individual flight paths. Instead, the 25th percentile, 50th percentile, and 75th percentile error for the wind fields on an hourly basis is used. If the 25th percentile hourly error is greater than 10 m/s, then 75% of all the errors measured in that hour are greater than 10 m/s. Given most of the errors in an hour are greater than 10 m/s, it is likely that the wind field for that hour would lead to poor ATM DST performance. If the 75th percentile error is large, only 25% of the reported errors in that hour are large, but if these errors tend to be located in one region of the airspace they may cause poor ATM-DST performance.

## 5. METHODOLOGY

To determine wind field accuracy, the wind fields are compared to a data set of independent ACARS wind measurements. More than one million ACARS reports collected during a one-year period (12 months for MIT/LL and 13 months for FSL) starting 1 August 1996 are used. These ACARS reports are collected in a region approximately 1300 km on a side that is centered on the Denver International Airport. Each ACARS report is independent of the RUC forecasts valid at the time the ACARS report was taken since it is taken after the data collection period for the RUC run. Similarly, the ACARS reports are independent of any AW field generated before the ACARS are taken.

The FSL results are obtained by differencing the ACARS reports with the RUC-1 and RUC-2 forecast fields nearest in time. The Lincoln results are obtained by taking the difference between each ACARS report and the most recent prior AW field and the difference between each ACARS report and the RUC-1 forecast used in that AW field. The wind field value at an aircraft location is computed from the gridded values using linear interpolation in three dimensions. The differences between ACARS and wind field values are estimates of the point errors in the wind fields and are used to compute the desired statistics.

The spatial distribution of the ACARS data is shown in figure 6. These data are from May 1st, 1997, the day United Airlines began rapid ascent and descent reporting in support of this study. The increased reporting continued through the remainder of the study period. Data prior to this have a similar distribution but are less dense, with about 3000 reports per day instead of about 8000. Most of the reports are at cruising altitudes, with two thirds of the reports associated with the grid levels at 200 mb and 250 mb. Approximately 11% of the reports are associated with levels at 300 mb and 350 mb. The remaining reports are roughly uniformly distributed among levels from 400 mb to 800 mb.

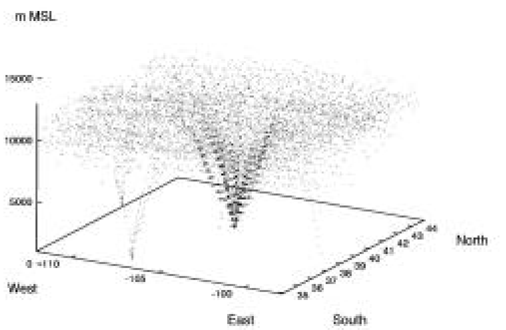



*Figure 6. Distribution of ACARS reports on 1 May 1997. This day has 8125 ACARS reports. This is after United Airlines increased their reporting rate.*

For these studies it is important to model the errors expected to be encountered by an ATM DST in computing time-of-flight as opposed to modeling random errors throughout the entire airspace. This is done by simply assuming that the distribution of ACARS in these studies is the likely distribution of aircraft an ATM DST will encounter. This means the reported accuracy statistics are not quite measures of the overall accuracy of RUC or AW. For example, these studies show that wind errors are greater at higher altitudes. Since there are more ACARS reports at higher altitudes, this tends to elevate the estimates of the RMS error in the wind fields relative to a uniformly distributed sample of errors. Conversely, there are more ACARS reports in regions where RUC and AW have dense data, perhaps reducing the error estimates.

## 6. RESULTS

FSL found a RMS vector error of 5.26 m/s over all 0-6 hour RUC-1 forecasts, and a RMS vector error of 4.67 m/s for the same forecasts for RUC-2. These values are corrected for the errors in the ACARS reports, and cover 13 months, doubling up on August. Lincoln found a RMS vector error of 6.24 m/s for RUC-1 3-5 hour forecasts and a RMS vector error of 4.51 m/s for the AW fields generated from these RUC-1 forecasts. These values are corrected for ACARS errors, and cover 12 months. A 16-day set of data were rerun using AW fed RUC-2 instead of RUC-1. The improvement due to AW over RUC is essentially the same using either RUC-1 or RUC-2, so the improvement presented for the year long AW data set should represent the AW improvement over RUC-2 as well as over RUC-1. While there is a reduction in RMS error due to the improvement in the RUC model and due to the augmentation with near real-time ACARS reports, all of these values are well below 10 m/s. However, significant errors exist within individual forecasts.

Figure 7 shows the percentage of point errors for RUC-1 and RUC-2 that are greater than 10 m/s on a month by month basis over 13 months, starting August 1996. The RUC-1 forecast fields are for predictions out 3-5 hours as the forecasts are not available prior to hour three after the start of the model run. The RUC-2 forecast fields for hours 1 and 2 are used, as these are available before an hour after the start of the model run. The percentage of large errors increases in the winter, corresponding to the increase in wind speed. Due to the combination of shorter forecast times and improved RUC, the RUC-2 produces far fewer large point errors than RUC-1, 8% vs. 3%, respectively.

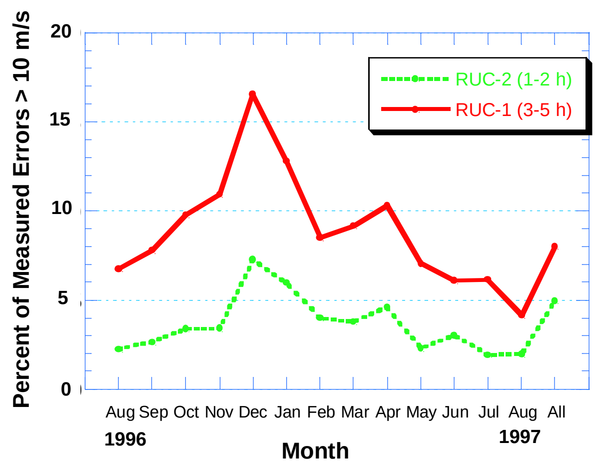



*Figure 7. RUC Monthly RMS vector errors greater than 10 m/s.*

Figure 8 provides probability distributions for RUC-1 and AW over the entire data set. For example, the 90th percentile wind vector errors are 10.18 m/s and 7.85 m/s, respectively. When the data are analyzed from the point of view of the large point error percentage metric, the figure indicates that RUC-1 forecasts contain vector errors greater than 10 m/s about 11% of the time, the AW enhancement reduces that occurrence to 4% of the time.

Table 1 presents results for the same data set, but using the third metric, large hourly error percentage. For comparison, the results are presented in terms of the 25th, 50th and 75th percentile hourly-vector errors. Considering the 25th percentile division, it is seen that there are 42 hours during the year when 75 percent of the RUC-1 vector errors exceed 7 m/s. These 42 hours are evenly divided between nighttime and daytime and usually occur as isolated hours. The results indicate that the AW enhancement reduces this number to five hours. There are no hours when 75 percent of the RUC-1 vector errors are greater than 10 m/s. Considering the 50th percentile division, the AW enhancement reduces the number of hourly vector errors greater than 7 m/s from 829 (RUC-1) to 124. Even more significant is the reduction of the number of hourly vector errors greater than 10 m/s from 46 hours to one. These 46 hours were also evenly divided between nighttime and daytime and usually occur as isolated hours. Having large errors even over 25 percent of a forecast region is potentially of operational concern if these errors are sustained along a flight path rather than randomly distributed. The AW enhancements resulted in similar improvements over RUC-1 for the 75th percentile division, but what is most notable is the reduction in the number of hourly vector errors greater than 15 m/s from 45 to 8. Again, these 45 hours are evenly divided between nighttime and daytime and usually occur as isolated hours.

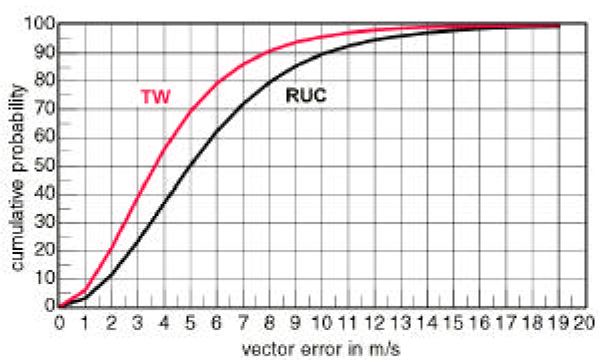



*Figure 8. RUC and TW cumulative probability vs. vector error.*

**Table 1. Number of hours with hourly Nth percentile vector errors above given thresholds. Results are for 7023 hours.**

| Variable | >7m/s | >10m/s | >15ms |
|---|---|---|---|
| RUC-1 25th percentile | 42 | 0 | 0 |
| AW 25th percentile | 5 | 0 | 0 |
| RUC-1 50th percentile | 829 | 46 | 0 |
| AW 50th percentile | 124 | 1 | 0 |
| RUC-1 75th percentile | 4160 | 834 | 45 |
| AW 75th percentile | 1913 | 203 | 8 |

## 7. CONCLUSIONS

Large wind errors (i.e., vector errors greater than 10 m/s) may be detrimental to ATM DST performance, especially if they persist along flight paths. Flight test results have demonstrated the existence of such large errors that are not captured by the classic RMS aggregate statistics typically used to assess the skill of wind-prediction systems.

Three types of metrics for measuring large errors were introduced. The first looks at the percentage of point wind vector errors greater than a threshold. The second type uses percentile values of the wind vector error, or the related probability distribution for wind vector errors. The last type is based on having a percentage of h errors above a threshold.

Two approaches to improving wind field accuracy, improving the numerical model, and updating forecasts with near real-time aircraft reports, were examined in a yearlong study of wind-prediction accuracy over the Denver Center airspace. Both approaches not only improved the overall aggregate RMS performance, they also greatly reduced the occurrence of large errors as measured by each of the three metrics. An additional analysis of a representative subset of sixteen days demonstrated the potential performance enhancements of combining both approaches simultaneously. The parameters that govern the AW algorithm were updated based on what was learned in this study. With the updated parameters, the improvement in RMS vector error of the augmented winds is essentially the same for both RUC-1 and RUC-2, so we feel that the above results for AW are relevant to use with the current operational RUC model. In other words, although RUC-2 provides a significant performance improvement over RUC-1 itself, an AW enhancement of RUC-2 adds additional performance on par with the AW enhancement of RUC-1.

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Dr. Cole received his B.S. in physics in 1981 and his M.S. in mathematics in 1982, both from the Virginia Polytechnic Institute and State University. He received his Ph.D. in mathematics from the University of Colorado in 1990. Dr. Cole began his research in meteorology at the National Center for Atmospheric Research in 1988 studying wind shear detection. He joined MIT Lincoln Laboratory in 1990, developing the wind shear detection algorithm for integrating the anemometer based LLWAS system and the radar based system TDWR, for the FAA. His work continues in wind estimation for the FAA Integrated Terminal Weather System.