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IMPACT OF PRE-DEPARTURE UNCERTAINTY ON COLLABORATIVE ROUTING COORDINATION TOOLS (CRCT) PREDICTION PERFORMANCE

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Abstract

The Collaborative Routing Coordination Tools (CRCT) Concept Demonstration and Evaluation Prototype is a set of tools to help the Federal Aviation Administration (FAA) detect traffic flow problems in advance, generate reroute-based problem resolutions, and evaluate the resolution strategies. CRCT does this by modeling four-dimensional aircraft trajectories and using them to predict demand for sector usage. CRCT predictions are affected by various sources of uncertainty in the National Airspace System (NAS). It is therefore useful to understand the contribution of this uncertainty to CRCT's predictive error. A methodology was developed to perform comparative prediction performance assessments of CRCT. Several performance metrics were defined and tools were developed to calculate the metrics from prediction data and actual track data. The metrics assess how closely predictions match the sector loads that actually occur. In earlier analyses the methodology was used to compare the predictive performance of CRCT under various software and data configurations. More recently it was used to assess the impact of pre-departure uncertainty on the prediction performance of CRCT. This paper describes CRCT trajectory modeling and sector load prediction, presents the methodology used to assess CRCT's prediction performance, and discusses the results of the pre-departure uncertainty analysis. This analysis is based on predictions made by CRCT for two Air Route Traffic Control Centers (ARTCCs). CRCT runs were made against recordings of actual air traffic data on two good weather days and two bad weather days.

Introduction

The FAA performs traffic flow management (TFM) to ensure the safe and smooth flow of traffic in the NAS. In order to do this, the FAA must monitor air traffic flows and NAS conditions. Flows are redirected as necessary to make them safe and smooth, that is, to balance capacity and demand while minimizing ground and airborne flight delays. While automation tools such as the Enhanced Traffic Management System (ETMS)[1] exist to support this function, additional capabilities could be used to further facilitate FAA provision of the TFM service. As a result, MITRE/CAASD has developed CRCT, an evolving prototype of tools to support early recognition of traffic flow problems, generation of reroute-based problem resolutions, and evaluation of the resolution strategies.

The CRCT prototype has been installed at the Kansas City (ZKC) and Indianapolis (ZID) ARTCCs and in the Air Traffic Control System Command Center (ATCSCC) where it is being evaluated. CRCT features that are deemed operationally mature are used to augment the capabilities of ETMS. Determination of the CRCT features that are to be implemented in ETMS is based in part on the results of field evaluations, laboratory exercises, and on prediction performance assessments of CRCT. Flow constrained area (FCA) and rerouting are examples of CRCT capabilities that have been approved for and are being implemented in ETMS[2].

CRCT models four-dimensional trajectories that predict the future behavior of aircraft. The trajectories and other data are used to predict and alert traffic management specialists when sector demand will exceed a preset threshold. When a TFM decision support tool (DST) such as CRCT predicts that demand for a sector will exceed its threshold, the specialist will typically act to prevent the overload. As a result, the sector load that is actually realized will tend to be smaller than the predicted demand. The difference between predicted demand and actual sector load is therefore not a measure of true predictive accuracy if any intervention is allowed between the prediction time and the time for which the prediction is made[3]. In spite of this, such a measure is adequate when used to compare the relative performance of a TFM tool under various configurations. Measures of this type have been used to identify CRCT capabilities that would improve the predictive accuracy of ETMS[4]. Similar measures were again used to perform the pre-departure uncertainty analysis that is reported herein.

It is well known that there is uncertainty in the NAS and that some of it is reflected in errors in the data DSTs use to model aircraft trajectories[5]. Since DST decisions are based on these trajectories, NAS uncertainty ultimately causes DST prediction errors. Using CRCT and established prediction performance metrics[4], CAASD assessed the impact of pre-departure

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uncertainty on CRCT sector load prediction error. The contribution of en route uncertainty was also assessed. The analysis was performed to support investment decision-making. Knowledge about the relative contribution of pre-departure and en route uncertainty to the prediction error can be used to make informed decisions about how to invest resources to improve predictive accuracy.

NAS DST developers have studied prediction error to understand the extent to which it is impacted by NAS uncertainty and to devise ways to account for the uncertainty when presenting DST decisions to the user. The User Request Evaluation Tool (URET), the NAS en route conflict probe, uses conformance boxes to make trajectories more stable and subsequently uses a measure of trajectory stability to determine how soon to notify the controller of a future conflict[6]. CRCT has been used to quantify uncertainty in TFM airspace demand predictions and to develop procedures that take this uncertainty into account when presenting information to the user[3]. NASA's Future ATC Concept Evaluation Tool (FACET) has been used to identify and rank error sources by their impact on sector demand prediction accuracy[5]. The FACET study also estimated the contribution of pre-departure and en route uncertainty to sector count error. In our analyses, we measure the contribution of both sources of uncertainty to two other metrics: sector entry error and hit rate. We also investigated the impact of uncertainty on the error in the predicted departure time.

CRCT Trajectory Modeling and Sector Load Prediction

CRCT obtains the data required to model aircraft trajectories from various sources. Flight plans and progress reports are received from ETMS. Flight plans, track data, and sectorization messages are optionally received from the local ARTCC Host. Wind forecast data is obtained from the National Weather Service (NWS) and adaptation data is obtained from ARTCC Adaptation Controlled Environment System (ACES) data, from National Flight Data Center (NFDC) data, from NAS facility letters of agreement (LOAs) and standard operating procedures (SOPs), and from aircraft manufacturer handbooks. The CRCT trajectory modeler builds the trajectory from planned departure time and route, current wind forecasts, departure airport delay statistics, aircraft performance characteristics, and known ATC procedures and restrictions.

CRCT trajectory modeling begins with the estimation of the flight departure time. This is initially the filed departure time. However, if the flight does not depart by this time, optional adaptive departure delay modeling can be used to update the departure time based on airport delay statistics. Next, the CRCT trajectory modeler uses the flight plan to determine the aircraft's lateral route of flight. The entire filed route is converted to a list of latitude/longitude pairs. No additional preferential routes are applied other than those already applied to the ETMS/Host flight plan. Turns in the route are modeled as being instantaneous. If track data exists for the flight and the track position is not on the cleared route, a set of rules is applied to determine how the aircraft will rejoin the route. The converted lateral route forms the initial set of trajectory nodes.

Next, the trajectory modeler determines the vertical profile of the trajectory. Altitude and speed are strongly coupled and both components of the trajectory are determined during this step. Altitude and speed restrictions, due to ATC procedures, are applied to the lateral route to determine constraints. CRCT then generates and inserts maneuver segments into the trajectory to satisfy these constraints. Segments are modeled to have constant acceleration and gradient, with instantaneous changes allowed at the endpoints.

Finally, the CRCT trajectory modeler assigns conformance bounds to each trajectory segment. Conformance bounds, which are used to support conformance monitoring, are specified in the lateral, longitudinal, and vertical dimensions. These bounds are smaller for level segments and larger for less predictable segments, such as those around turns and during vertical transition. The conformance monitoring function ensures that the trajectory is maintained within acceptable conformance bounds. When an aircraft's track is updated, the track position is compared to the conformance bounds around the current trajectory segment. If the track position is outside the conformance bounds, the trajectory is updated to reflect observed aircraft behavior (short-term position and heading, speed, and climb or descent rate).

CRCT uses the modeled aircraft trajectories and airspace adaptation data to generate sector transits, which are in turn used to predict sector loads. Predictions are normally made each hour for 15-minute intervals at lookahead times that are up to six hours in the future. The sector load prediction for an interval represents the maximum instantaneous aircraft count for that sector. The prediction performance metrics, reported herein, reflect differences between predicted and actual sector transits. Lower level trajectory accuracy metrics, not reported herein, are based on differences between predicted aircraft trajectories and their actual track. Although not as sensitive to error as the trajectory accuracy metrics, the prediction performance metrics are used because they are more operationally meaningful. Trajectory accuracy metrics are typically used to diagnose and correct flight trajectory problems. The two types of metrics are

correlated however. An improvement in trajectory accuracy will result in no observable change or in improved prediction performance, but will not result in degraded performance.

Prediction Performance Assessment

Prediction performance analysis of CRCT entails determining how closely CRCT predictions about aircraft behavior match the observed behavior of the aircraft, calculating operational metrics from these differences, and comparing the metrics for alternative CRCT data/software configurations. The analysis is based on recorded air traffic data, also known as scenario data. Since the scenario data includes controller interventions between prediction and event times, the analysis results tend to underestimate the true predictive accuracy of CRCT. CRCT predictions are made from trajectories that are modeled from flight plans and amendments contained in the scenario. Actual aircraft behavior is determined from track reports, which are also contained in the scenario.

Figure 1 illustrates the process that is used to conduct prediction performance analysis of CRCT. The process begins with a CRCT run against an air traffic scenario that consists of recorded ETMS data. After the CRCT run is made, a data extraction and analysis tool (DEAT) is run against Host data from the ARTCC for which CRCT predictions were made. During the CRCT run, predicted sector transit records are collected and during the DEAT run, actual sector transit records are collected. Transit records are input to the transit record analyzer (TRA), which calculates error in CRCT's predicted transits. Finally, a data stratification and aggregation tool (DSAT) is used to stratify and aggregate TRA measures to produce operational performance metrics for predictions from multiple CRCT runs. These results can then be compared to assess the relative performance of CRCT predictions in all runs.

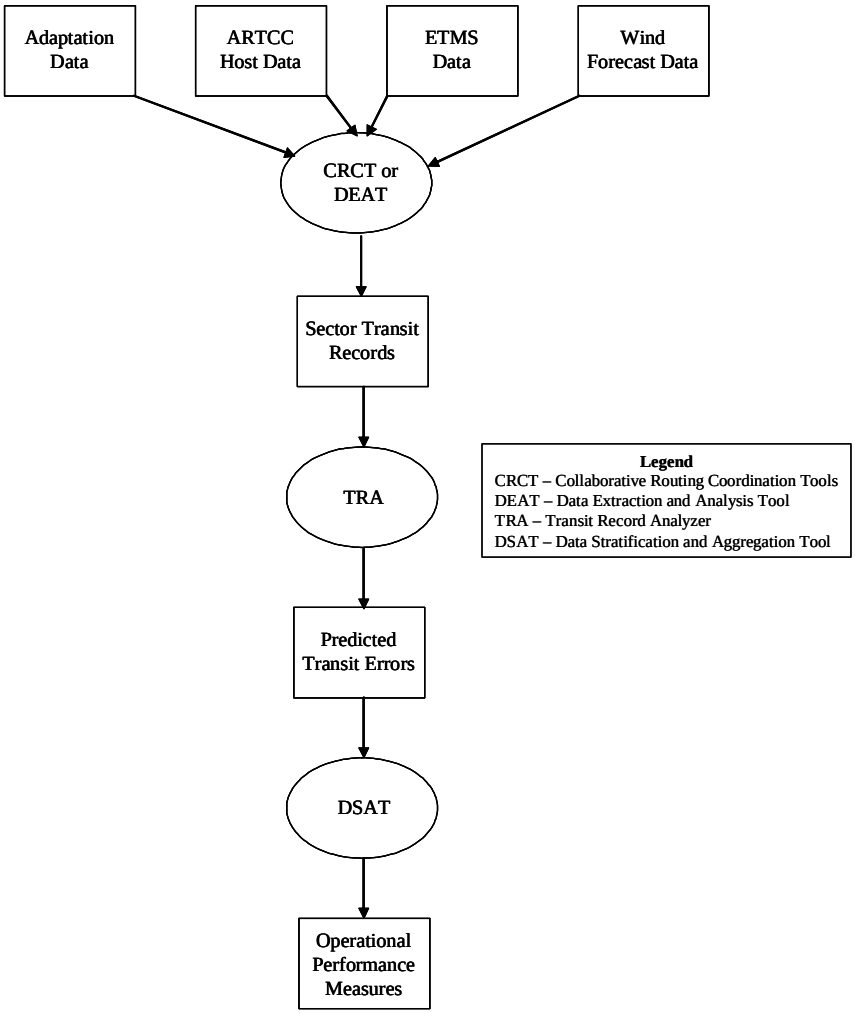

Figure 1. Prediction Performance Assessment Process, Tools, and Data

CRCT operational performance metrics characterize the accuracy of the CRCT predictions that are displayed or noticeable to the user. These metrics consist of sector count error, sector entry error, sector dwell error, and hit rate. Predicted and actual sector transit records are used to calculate these measures. Sector transit records consist of the flight and sector IDs and the sector entry and exit times. Attributes such as flight type, sector type, and lookahead time are used to stratify the metrics. The lookahead time is the difference between the time at which the prediction is made and the time for which the prediction is made. The mean and other available statistics are determined as an aggregation of the operational performance measures.

The computation of some metrics requires matching predicted and actual data for a given flight. This becomes difficult when a flight is late and there are multiple flight legs between an origin-destination pair for which the same aircraft identification is used. To avoid this problem, predicted and actual sector entry times are required to be within an hour of each other. This tends to limit the difference between predicted and actual sector transit records from which the prediction performance metrics are determined. The metrics are nevertheless useful in comparing the relative performance of CRCT under alternative data and software configurations.

Sector Count Error is the difference between the CRCT-predicted and the actual aircraft count for a sector during a one-minute time bin. The mean absolute error is calculated for all CRCT-predicted sector counts. Other statistics such as mean and variance are available. The error is stratified by lookahead time and can be stratified by sector type (low, high, and super-high altitude). It should be noted that a zero sector count error does not necessarily imply good prediction performance. For example, CRCT could correctly predict the number of flights that will occupy a sector during a time interval, but the prediction could be based on the wrong flights.

Sector Entry Error is the difference between the CRCT-predicted time and the actual time that an aircraft enters a sector. Predicted and actual transit records are first matched. The mean sector entry error is calculated for all sector entry times predicted by CRCT. While this statistic is used because it allows easy identification of bias, others are available. The error is stratified by lookahead time and can be stratified by flight type (active and proposed).

Sector Dwell Error is the difference between the CRCT-predicted and the actual time that an aircraft spends in a sector. Predicted and actual transit records are again matched. The mean absolute error is calculated for all CRCT-predicted sector dwell times. Again, other statistics are available. The error is stratified by lookahead time and can be stratified by flight type.

There are two types of Hit Rate. Matching predicted and actual transit records are used to calculate both types. Predictive hit rate is the fraction of flights predicted to enter a sector that actually do enter the sector. Actual hit rate is the fraction of flights that enter a sector that were predicted to enter the sector. The complement of the actual hit rate is the missed prediction rate and the complement of the predictive hit rate is the false prediction rate. The mean hit rate is calculated for all CRCT-predicted and for all actual sector transits. Hit rate is stratified by lookahead time and can be stratified by flight type.

Since CRCT prediction performance assessment methodology is scenario based, assessment results may vary depending on the scenario day used. The methodology also does not address sampling questions, such as the size of a statistically significant sample or the correlation between sample points. Assessment results and conclusions drawn from them should be interpreted in this context. Additional analyses (non-prediction performance and prediction performance using more scenarios) should be performed to validate the conclusions reached from prediction performance assessments.

Pre-Departure Uncertainty Analysis

The pre-departure uncertainty analysis was based on CRCT predictions of ZID and ZKC sector loads for four days. ZID and ZKC CRCT runs were made for each day using the day's ETMS, wind forcast, and adaptation data as input. No ARTCC Host data was used for the CRCT runs. Actual sector loads, to which the predicted loads were compared, were obtained from ARTCC Host data. The following sections describe the scenario days, discuss the analyses that were performed, and present the results.

Scenarios

The scenario days used for the analysis are 24 and 27 January 2003, two good weather days, and 13 and 20 March 2003, two bad weather days. Figure 2 illustrates weather radar images for one hour on each of the four days. On the good weather days, the few pockets of convective weather that existed were fairly light and outside of ZID and ZKC, and consequently were not expected to affect flows to the ARTCCs. On 24 January, due mainly to equipment failure, there were short ground stops at a few airports in the Eastern U.S. On 27 January, because of winds there was a lengthy ground delay program at LaGuardia Airport (LGA).

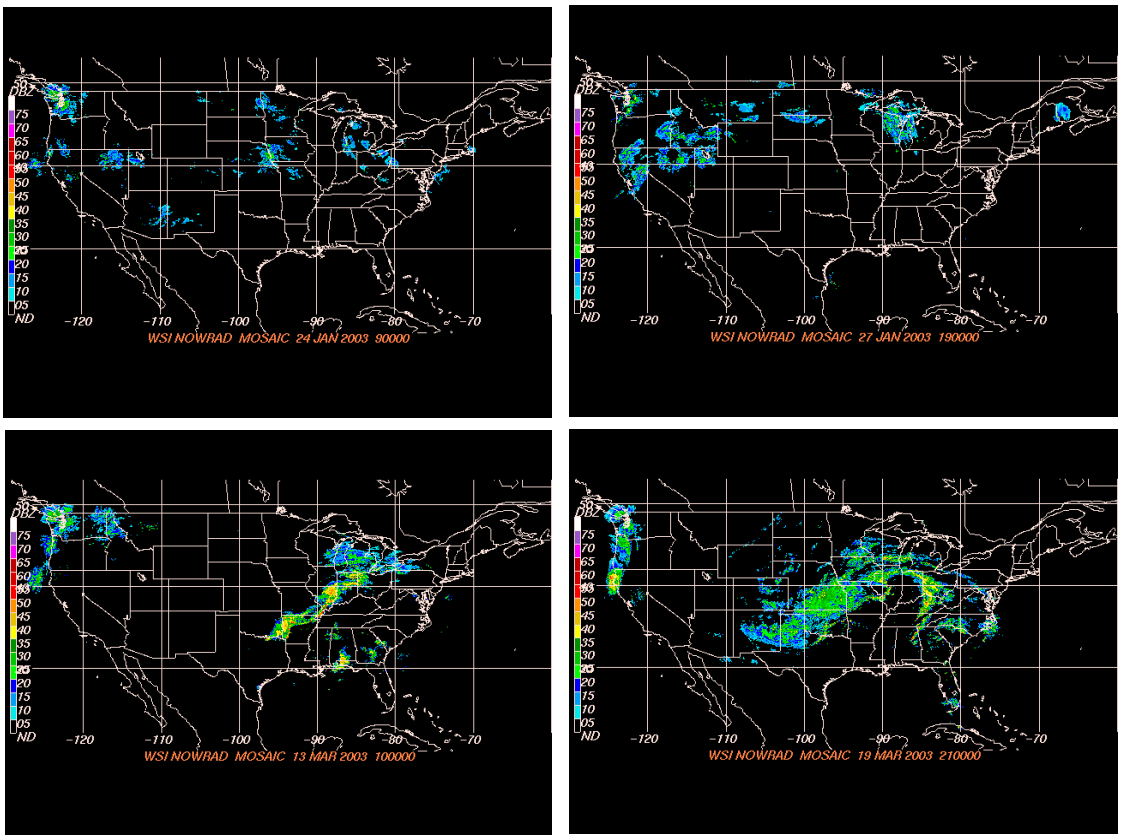

Figure 2. Weather Radar Images for Good and Bad Weather Days

There was no playbook reroute* on either good weather day.

On 13 March, the first bad weather day, a diagonal band of convective weather moved east across the U.S., passing through ZID and ZKC on its way. There were ground delays, ground stops, and cancellations at one west coast airport and seven in the eastern and midwestern U.S. Four playbook reroutes were in effect at Dallas Fort Worth (DFW) and Houston (IAH) International Airports. These flow management initiatives affected the flow of flights to ZID and ZKC. On 20 March, there were large clusters of convective weather in the East and Midwest. There were ground delays, ground stops, and cancellations at six major airports in this region. There was no playbook reroute. The schedule disruptions affected flights to ZID and ZKC.

Table 1 presents the counts of the significant ETMS message types processed by CRCT on the four scenario days. Air carriers send airline flight messages to ETMS to inform the automation of schedule changes. These changes are needed by ETMS and CRCT as they obviously impact predictions at longer lookahead times. NAS flight plans and amendments are used to model trajectories, which are the basis of ETMS and CRCT predictions. Flight control messages are used to implement or modify ground delay and ground stop programs and consequently impact flight departure times. Flight plan cancel messages include airline and NAS messages to cancel flights. Arrival and departure messages are used by TFM automation tools to update flight status. Position updates are also used to update flight status, but are additionally used for trajectory conformance monitoring.

Table 2 presents the counts of commercial, general aviation (GA), military, and other flights that entered ZID or ZKC airspace in the four scenarios. Flights in the 'other' category consist of Canadian GA, air taxi, and lifeguard flights. The flights that are counted in Table 2 are the subset of the ETMS flights whose observed sector transits are the truth to which CRCT's predicted transits are compared.

* The FAA's National Playbook is a collection of pre-defined reroutes that can be quickly coordinated and implemented to route traffic away from areas impacted by severe weather.

Table 1. ETMS Message Counts on Scenario Days

ETMS Message	24 January	27 January	13 March	20 March
Airline Flight	118288	119358	133221	124246
NAS Flight Plan/Amendment	408546	376498	431127	429553
Flight Control	1079	5629	7683	25601
Flight Plan Cancel	8113	6909	7763	9764
Arrival	48779	42552	48716	47304
Departure	56905	50389	57060	55774
Position Update	5014126	4557046	5030773	4909287
Oceanic Position Update	4822	4666	4808	4569

Table 2. ZID/ZKC Flight Counts on Scenario Days

Aircraft Type	24 January	27 January	13 March	20 March
Commercial	8189	7175	8523	8412
General Aviation	1517	1418	1829	1855
Military	344	303	281	280
Other	54	57	69	83
Total	10104	8953	10702	10630

Scheduled and Filed Flight Plans

The prediction performance of CRCT was compared when predictions were based on scheduled flight plans and when they were based on filed flight plans. Performance metrics were calculated for matching last scheduled and first filed flight plans. Scheduled flight plans are derived from historical data for flights listed in the Official Airline Guide (OAG). Since this data is available for commercial flights only, the prediction performance comparison for scheduled and filed flight plans is limited to airline data.

Figure 3 illustrates CRCT mean absolute sector entry error for scheduled and filed flight plans on good and bad weather days. The error is presented as a function of time to departure. Sector entry error is comparable for scheduled and filed flight plans, suggesting that, in terms of this metric, filed flight plans do not provide better prediction performance than scheduled plans. Departure time error, which is the major factor that impacts sector entry error, is shown in Figure 4. Not surprisingly, departure time error is comparable for last scheduled and first filed flight plans.

Figure 5 presents CRCT predictive hit rate for last scheduled and first filed flight plans on good and bad weather days. Unlike sector entry error and departure time error, there is a noticeable difference between hit rate for scheduled and filed flight plans. Hit rate is higher for filed flight plans meaning that more flights actually enter the sectors they are predicted to enter when the predictions are based on filed plans than when they are based on scheduled ones. Since estimated departure times are similar for scheduled and filed flight plans (Figure 4) the vertical profiles for the corresponding (scheduled and filed plan) trajectories are expected to be similar. This suggests that the observed difference in the hit rate is due to differences in the lateral route specified for corresponding scheduled and filed flight plans.

Figure 6 illustrates the distribution of the pre-departure time at which flight plans are filed (for commercial aircraft) at both (ZID and ZKC) ARTCCs. Approximately half of all flight plans are filed by 90 minutes to departure. When this occurs, the routes for the flights are known more accurately, however the flying time to sectors is no more accurate.

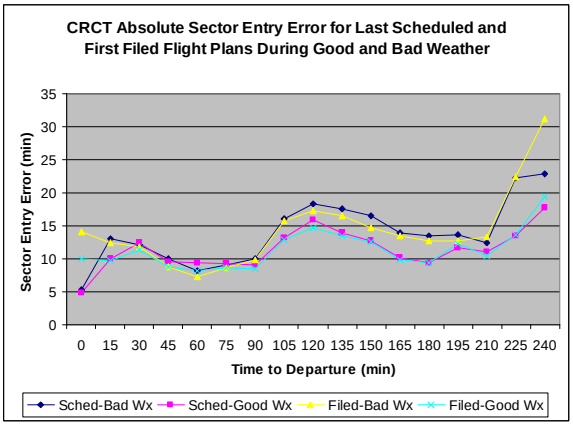

Figure 3. CRCT Sector Entry Error for Scheduled and Filed Flight Plans

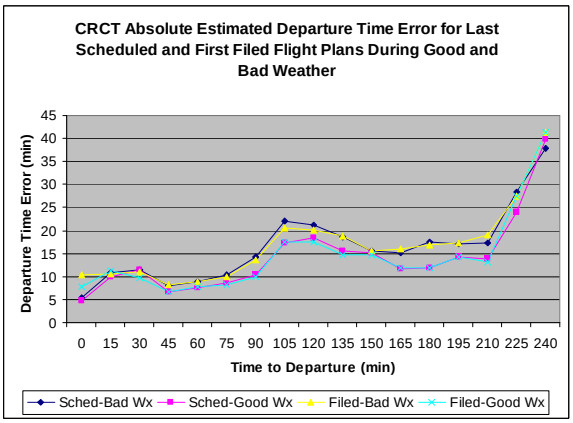

Figure 4. CRCT Departure Time Error for Scheduled and Filed Flight Plans

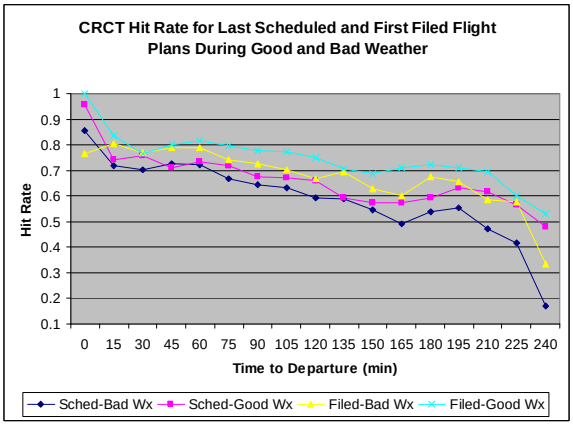

Figure 5. CRCT Hit Rate for Scheduled and Filed Flight Plans

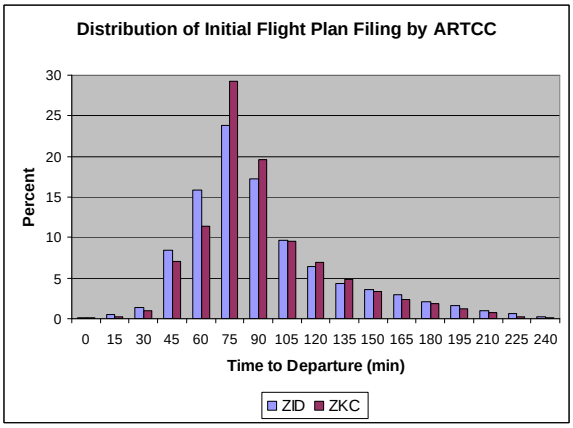

Figure 6. Distribution of Flight Plan Filing Time

Controlled Flights

CRCT prediction performance metrics were compared for commercial flights with filed flight plans and flights with controlled departure times. Flights with controlled times had an estimated departure clearance time (EDCT) at the time of the prediction, though the EDCT may have been subsequently cancelled. EDCTs are assigned as part of ground delay programs which are usually implemented during bad weather. For this reason, the comparison is performed using the bad weather scenarios only.

Flights typically depart at or after their planned times. CRCT departure time estimates, sometimes based on adaptive delay logic, like the planned times, are usually earlier than the actual departure times. During bad weather, departure time uncertainty is greatest for controlled flights and Figure 7 shows that the absolute error in estimated departure time is largest for these flights. As Figure 8 shows, sector entry error is also greatest for controlled flights. This is expected because pre-departure error is the dominant component of sector entry error. While estimated departure time error and sector entry error metrics are worse for flights with controlled departure times, Figure 9 shows that hit rate is best for these flights up to approximately two and one half hours prior to departure and best for flights with filed plans beyond that pre-departure time. This suggests that some of the flights with controlled departure times had their routes amended.

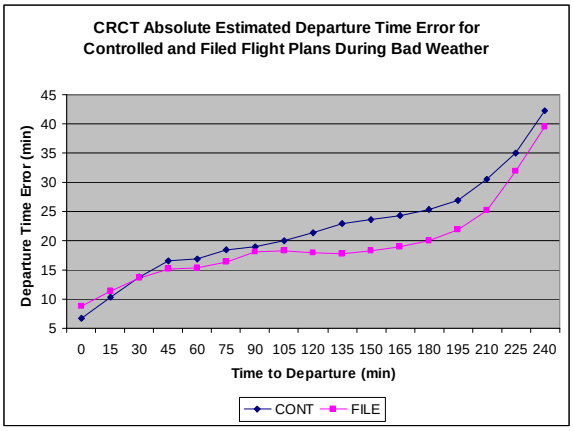

Figure 7. Departure Time Error for Controlled Flights

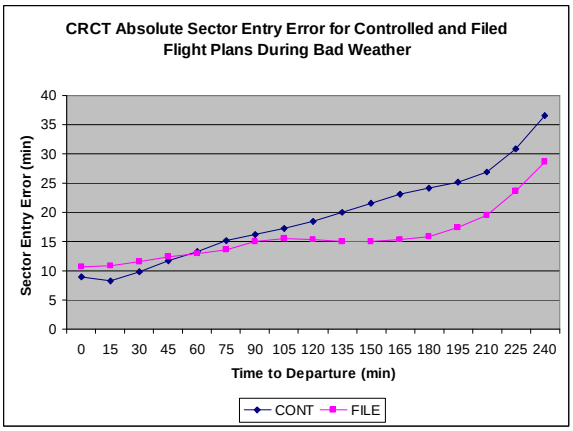

Figure 8. Sector Entry Error for Controlled Flights

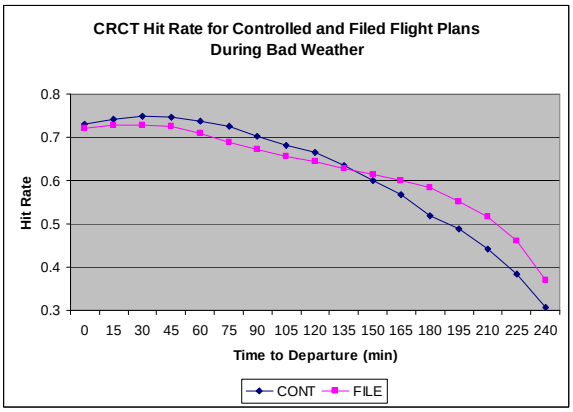

Figure 9. CRCT Hit Rate for Controlled Flights

Ground delay programs are sometimes cancelled allowing controlled flights to depart before their EDCTs. This can impact the prediction performance of CRCT. CRCT departure time error, sector entry error, and hit rate were compared for controlled flights that did and did not have an EDCT at wheels up time. Since more flights are expected to have EDCTs during bad weather than during good weather, the comparisons were performed using the bad weather scenarios only.

As with a general set of flights, CRCT generally predicts that controlled flights depart earlier than they actually do. Figure 10 shows that CRCT departure time estimates are more accurate for controlled flights that still had an EDCT at wheels up. This is also the case for sector entry error, as Figure 11 demonstrates. Mean absolute sector entry error is greater for flights with no EDCT at wheels up than for flights with EDCT at wheels up. CRCT typically predicts that flights enter sectors earlier than they actually do. This is the case for controlled flights with EDCTs at wheels up. However, Figure 11 shows that for controlled flights with no EDCT at wheels up CRCT tends to predict that the flights enter sectors later than they actually do in predictions made up to two and one half hours before departure. Figure 12 shows that, like departure time error and sector entry error, CRCT hit rates exhibits the best performance for controlled flights with EDCTs at wheels up. The routes for controlled flights whose EDCTs were still active at wheels up are a more accurate representation of intent than for those with no EDCT at wheels up.

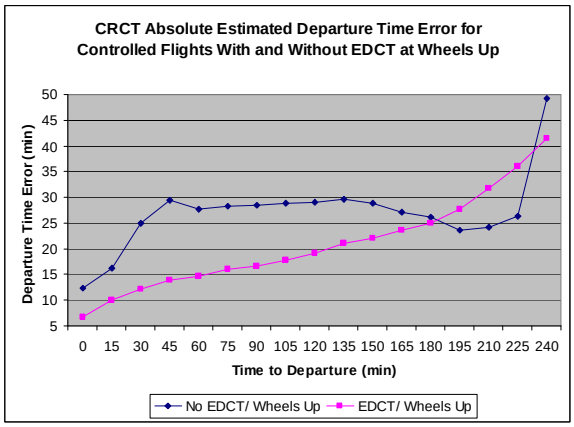

Figure 10. Departure Time Error for Flights With and Without EDCTs

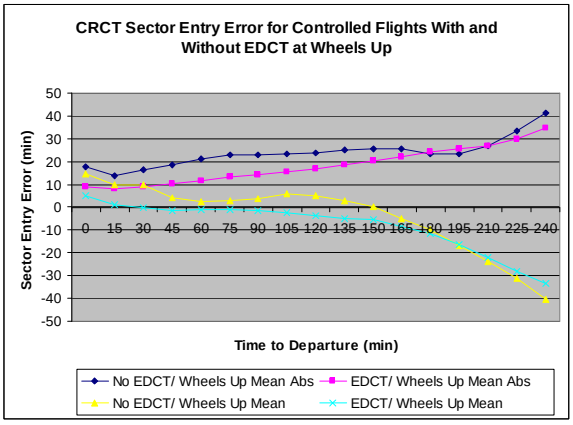

Figure 11. Sector Entry Error for Flights With and Without EDCTs

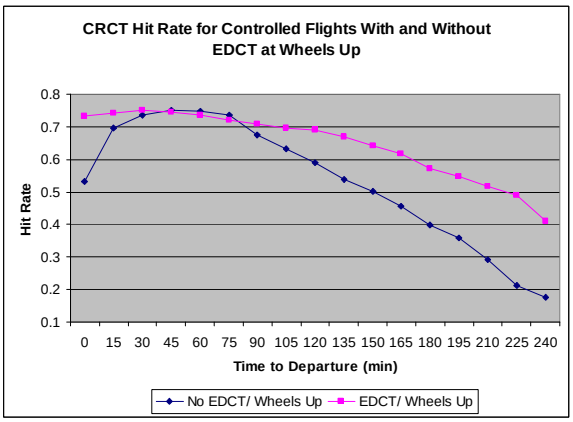

Figure 12. CRCT Hit Rate for Flights With and Without EDCTs

Pre-Departure Component of Prediction Error

Sector entry error was determined for proposed commercial flights at various times before departure and for newly active flights for various flight times to sector. The difference between sector entry error for proposed and active flights is used to estimate the pre-departure component of the prediction error while sector entry error for active flights is used to estimate the en route component. We make the simplifying assumption that the sum of the absolute pre-departure and en route errors is equivalent to the total sector entry prediction error. Pre-departure and en route errors were aggregated by weather day and the relative contribution to the total was determined.

Figure 13 presents the total CRCT sector prediction error, aggregated for ZID and ZKC, as a function of time to departure during good weather and bad. Figures 14 and 15 illustrate the contribution of pre-departure and en route errors to total predictive error, on good and bad weather days, respectively. Each curve in the figures represents a given flight time to sector and presents pre-departure contribution to total error by time to departure. Flight time to sector is expressed in 15-minute quantiles, with the 0 quantile representing flight times up to 14 minutes. The pre-departure component dominates the sector prediction error on good and bad weather days. As to be expected, pre-departure portion of the error decreases as flight time to sector increases. On bad weather days, the relative contribution of pre-departure uncertainty to the total prediction error is slightly more than on good weather days.

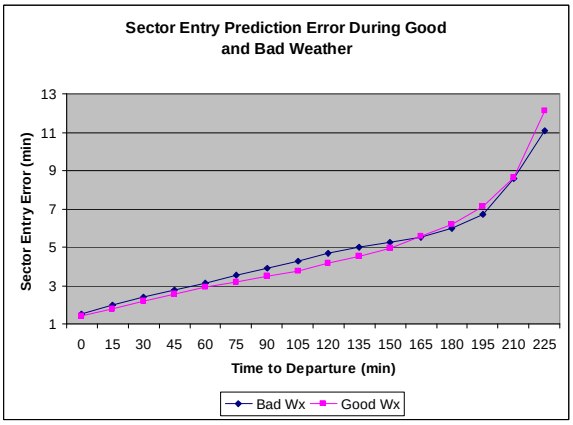

Figure 13. Sector Entry Prediction Error During Good and Bad Weather

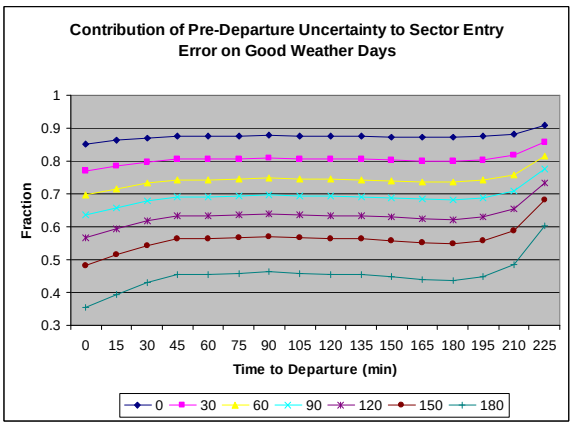

Figure 14. Pre-Departure Component of Sector Entry Error for Good Weather

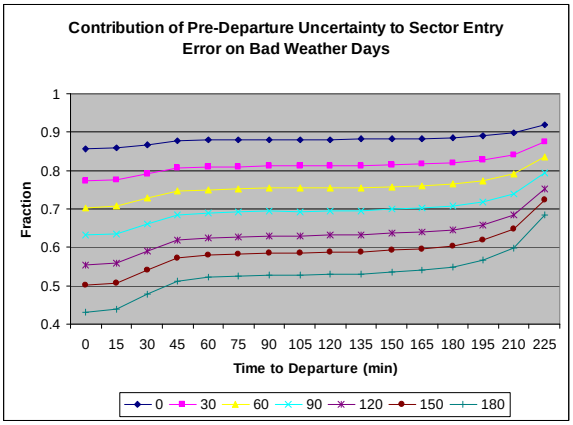

Figure 15. Pre-Departure Component of Sector Entry Error for Bad Weather

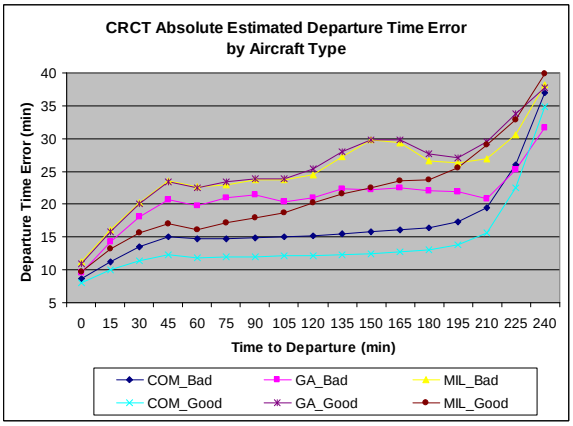

Figure 16. CRCT Departure Time Error by Aircraft Type

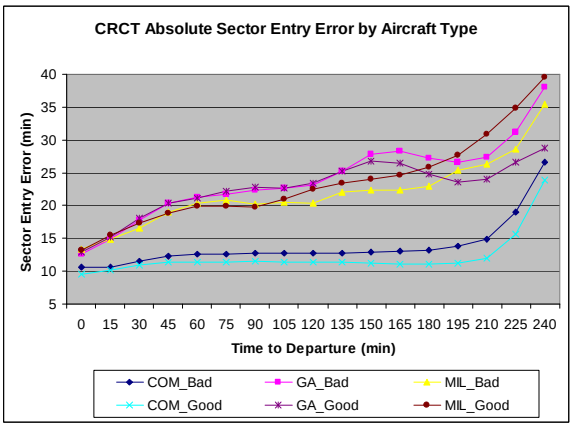

Figure 17. CRCT Sector Entry Error by Aircraft Type

Commercial, General Aviation, and Military Flights

Pre- and post-departure prediction accuracy was investigated for commercial, general aviation (GA) and military flights. Sector entry error, predictive hit rate, entry error, and error in estimated departure time were determined for proposed flights of each type as a function of time to departure. The same metrics were also determined for active flights of each type as a function of flight time to sector.

Commercial aircraft are driven by financial incentives to meet their schedules while GA and military aircraft are not. It is to be expected that departure times are more easily estimated for commercial flights and consequently sector entry error would be lowest for these flights. This is indeed the case as Figures 16 and 17 illustrate. Figure 16 shows that on both good and bad weather days CRCT estimated departure time error for commercial flights is less than for GA and military aircraft. Estimated departure time error is less on good weather days than on bad weather days for commercial and military aircraft. Surprisingly, the opposite is the case for GA aircraft. This warrants further investigation. There are more GA flights on the bad weather days (Table 2) but the nature of the flights might differ on good and bad weather days. For example, there are probably a smaller percentage of recreational GA flights (possibly with greater flight plan data uncertainty) on bad weather days.

Figure 17 illustrates that, since estimated departure time error is smallest for commercial flights, sector entry error is also smallest for these flights. For commercial aircraft, sector entry error is less on the good weather days than on the bad weather days. For GA and military aircraft, sector entry error is comparable on good and bad weather days for pre-departure times up to approximately two hours. Beyond that time, sector entry error for GA aircraft is less on the good weather days. For pre-departure times of two hours and beyond, sector entry error for military aircraft is less on the bad weather days, a counterintuitive result. This again is a candidate for further study. The sample of military flights is relatively small (Table 2) making prediction performance metrics for those flights more susceptible to outlier influences.

Figure 17 presents total prediction error by aircraft type for good and bad weather days. Figures 18 and 19 illustrate the contribution of pre-departure and en route errors to the total for good and bad weather days,

respectively. Each curve in the two figures presents pre-departure contribution to total predictive error for commercial, GA, or military aircraft and for 60 or 120 minutes flight time to sector. Except for military flights with two hour flight time to sector, the pre-departure component dominates the predictive error on both good and bad weather days.

Figure 20 illustrates CRCT hit rate by aircraft type for good and bad weather days. Hit rate is higher on good weather days for each aircraft type, suggesting, not surprisingly, that flight plan routes more accurately reflect the path aircraft take on good weather days. Hit rates are best for commercial aircraft, except at pre-departure times up to 90 minutes, at which times GA hit rate is comparable or slightly better.

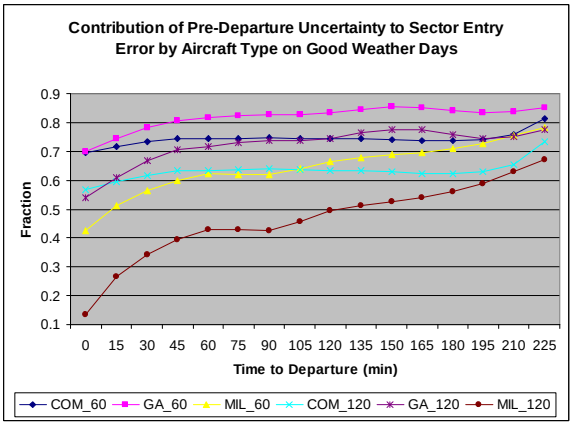

Figure 18. Pre-Departure Component of Prediction Error During Good Weather

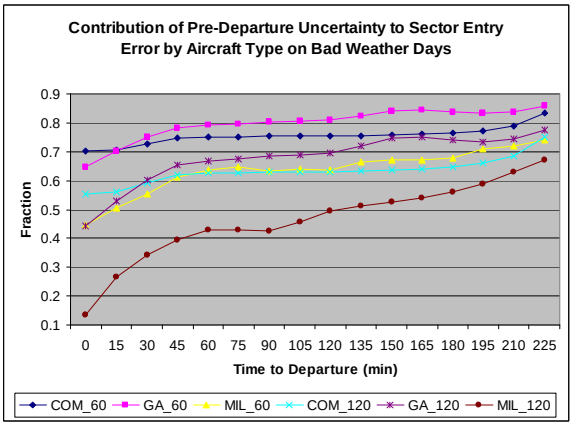

Figure 19. Pre-Departure Component of Prediction Error During Bad Weather

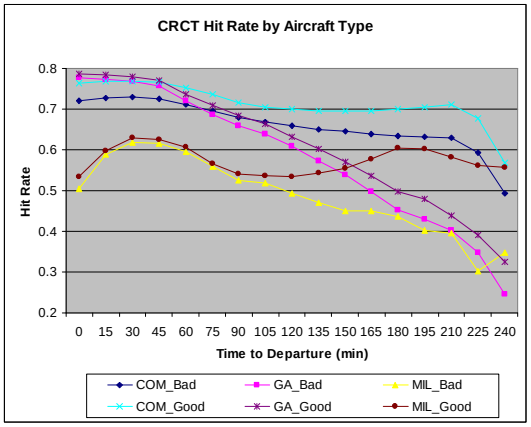

Figure 20. CRCT Hit Rate by Aircraft Type

Summary and Conclusion

A prediction performance analysis was done to assess the contribution of pre-departure uncertainty to CRCT's sector prediction error. The analysis was based on CRCT predictions for ZID and ZKC on two good weather days and two bad weather days. The metrics, estimated departure time error, sector entry error, and hit rate, were calculated at various times before departure.

A comparison of CRCT's prediction performance when scheduled and filed flight plans were used for commercial aircraft showed that estimated departure time error and sector entry error were comparable when based on the last scheduled or first filed flight plan. However, hit rate was better for first filed flight plans suggesting that the flight plan route was amended for some flights when their initial flight plans were filed. Approximately one half of initial flight plan filings are made by 90 minutes before departure.

CRCT prediction performance was compared for commercial flights with and without controlled departure times during bad weather. As expected, estimated departure time error and sector entry error were greatest for flights with EDCTs. However, hit rate was best for controlled flights at pre-departure times up to two and one half hours. This probably means that some flight plan routes were amended after the flights were given controlled departure times. Prediction performance was also compared for controlled flights that still had EDCTs at wheels up and that no longer had an EDCT at wheels up. Estimated departure time error, sector entry error, and hit rate were all better when the EDCT was still in effect at wheels up.

The pre-departure component of the CRCT prediction error (sector entry error) was assessed for commercial flights as a function of time to departure and flight time

to sector. As one might expect, the fraction of the prediction error due to pre-departure error decreases as flight time increases. For a given flight time, the fraction is fairly constant at most pre-departure times, with noticeable increases at the earliest and latest times.

CRCT prediction performance was compared for commercial, GA, and military flights. Estimated departure time error and consequently sector entry error was least for commercial flights. This is understandable given the incentives that commercial flights have to be punctual. Except for military flights with long flight times to sector, the pre-departure component dominates the predictive error. Hit rate is best for commercial flights and is better on good weather days than on bad.

The prediction performance analyses have shown that pre-departure uncertainty is a greater contributor to CRCT's sector prediction error than en route uncertainty. Research is recommended to determine more accurate estimates of aircraft departure time. Airline submission and ETMS use of early intent messages should improve departure time accuracy. Historical data could be analyzed to estimate departure delay as function of several variables, including departure airport, type of weather, and type of flight. Use of this data should reduce estimated departure time error. Airport surface automation is needed to monitor aircraft before take-off, update estimated departure times, and forward them to other NAS automation. It should be noted however that, while these departure time estimates may be very accurate, the lookahead time at which they are available may be too short to make them useful to TFM tools.

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