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ANALYSIS OF EN ROUTE SECTOR DEMAND ERROR SOURCES

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Abstract

We present results of a detailed investigation into the error sources associated with en route sector demand prediction. Our analysis is based on interviews with air traffic controllers and personnel from the Air Traffic Control System Command Center (ATCSCC), aggregate data collected over the National Airspace System (NAS), and observations and data collected from on site visits to two en route center facilities (Chicago ZAU and Cleveland ZOB). Potential error sources are ranked in terms of their influence on sector demand prediction accuracy. Sector demand prediction data was generated using NASA's Future ATC Concept Evaluation Tool (FACET) to predict future trajectories. Enhanced Traffic Management System (ETMS) and Aircraft Communications Addressing and Reporting System (ACARS) data were used for truth data. Given these data, both detailed and aggregate characteristics of errors in sector entry time and sector demand were analyzed. Results indicate several areas where computer readable input data sources are needed and where future research should be directed to improve our ability to predict sector demand.

Introduction

The lack of accurate en route sector demand prediction has historically been an obstacle to the improvement of Traffic Flow Management (TFM) for en route segments of NAS. In this paper, we characterize and quantify the error sources responsible for the lack of accuracy.

In our work, we have investigated several potential sources for error, as illustrated in **Table 1**. Through a combination of interviews with controllers and researchers, we have ranked these error sources in terms of their influence on the prediction problem. Factors range from those that are predictable, but don't occur very often, to those that are completely unpredictable, yet occur often. The most critical factors were classified into the areas of departure time prediction and prediction of TFM initiatives and ATC actions. Examples for departure time prediction include: abnormal surface events (runway and taxiway closures, obstructions on runways or taxiways, snow and/or ice removal, de-icing operations, runway direction reversals), unavailable gates, lack of information about General Aviation (GA) aircraft (e.g., pop up aircraft that do not have filed flight plans when they take off), the effects of adverse weather, and accidents/incidents[6]. Examples for predictions of TFM initiatives and ATC actions include: non-standard procedures across sectors and centers, style and preferences of controllers, lack of data on TFM initiatives or ATC actions (procedures typically avoid unnecessary data entry), daily trends[10] due to weather and congestion, and seasonal trends.

In our investigation, we use NASA's FACET[3] to determine trajectory predictions and sector demand predictions in the NAS. FACET has been developed by NASA Ames Research Center to address a spectrum of Air Traffic Management (ATM) issues. FACET has the capability to model NAS-wide operations and strategic TFM issues. FACET is based on a detailed flight simulation capability. Flight trajectories are modeled using a spherical Earth trajectory model, including forecasted wind effects. Simulated flight routes follow the filed flight plan. Climb to the filed cruising altitude, and descent from altitude, are modeled through the use of performance parameters that are stored in look-up tables.

Table 1. Error Sources and their Level of Influence on Sector Demand Prediction.

Influence	Error Source
High	Departure Time Prediction
	Prediction of TFM Restrictions and ATC Actions
	Horizontal Route Prediction Accuracy
Medium	Vertical Route Prediction Accuracy
	Flight Speed Prediction Accuracy
	Changing Airspace Adaptation Data
	Weather and Winds Aloft Forecast Accuracy
Low	Accuracy of Surveillance Data
	Flight Technical Errors and Operational Errors
	Accuracy of the Trajectory Models

Analysis of Sector Demand Errors

In our analysis, we only investigate the error sources that we determined to have a high influence on sector demand prediction accuracy. Namely, we focus our investigations on departure time prediction and the effects of TFM restrictions and ATC control actions. The literature[1,4,7,8,11] covers many aspects of trajectory prediction and trajectory prediction accuracy. However, instead of trajectory predictions, we study sector demand. We analyze two metrics:

- Sector entry time, and
- Sector count.

Also, we break down the analysis into two different types of predictions:

- **Active flights** – these flights are currently en route when the prediction is made.
- **Proposed flights** – these flights are currently on the ground when the prediction is made.

Sector Entry Time. In this section, we consider the accuracy of FACET in predicting sector entry events. In **Figures 1** and **2**, the signed and absolute sector entry time prediction errors are plotted for proposed and active flights for ZAU and ZOB airspaces. The signed sector entry time is the predicted minus the actual time of entry into a sector. The absolute sector entry time is the absolute value of the predicted minus the actual time of entry. The absolute active sector entry time errors exhibited increased error as look-ahead time increases. Over the 5 days that we studied, the sector entry time error for ZOB is almost always larger than ZAU results, at lease with look ahead times up to 120 minutes.

Absolute sector entry time errors for proposed flights appear to get better as look ahead time increases up to look ahead times of 80 to 100 minutes, then proceed to get worse. This is because there are relatively few unique flights that make up the proposed flight data points with short look-ahead times. These few flights that make up the early part of the proposed curve are heavily biased towards data anomalies. Until very recently (a recent patch in the Host computers is now being made), the ETMS[5] TZ altitude data included a high number of temporary T-altitudes which describe where a controller directed an aircraft to go rather than where an aircraft actually is located. Because of this, a large error in altitude caused an error in sector entry time. Also, we receive very few flight amendments less than a half hour before take off which translates into no new information with which to improve trajectory predictions for short look ahead times.

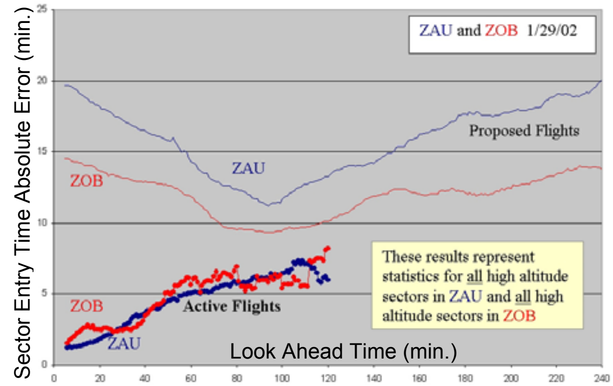

Figure 1. Absolute Sector Entry Time Error for predictions of proposed and active flight for ZAU and ZOB on 1/29/02.

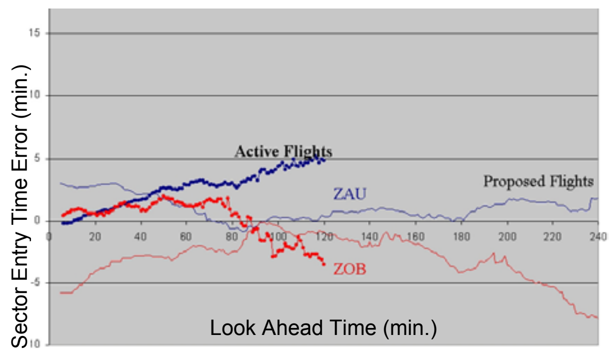

Figure 2. Signed Sector Entry Time Error for predictions of proposed and active flight for ZAU and ZOB on 1/29/02.

These plots indicate the trends in sector entry time predictions over two adjacent centers. The following general points can be made:

- Active flights generally have an error plot that is fairly linear starting near zero with very small look-ahead times.
- In general, ZOB has a tendency to have less error than ZAU. One possible explanation for these results is that ZAU contains Chicago O'Hare (ORD) airport, one of the most congested airports in the NAS where there is often unexpected airborne holding. Such holding, as discussed later in this paper, is a major source of sector demand error.
- In all of our on-site visit observations, the active performance metrics are significantly better than the proposed ones. This is expected because with active flights we have a known departure time that is the greatest source of error for trajectory prediction of proposed flights.

Sector Count. Sector count prediction is the ability of a tool to predict for any sector the number of aircraft to be in that sector at some time in the future. Predicted sector counts allow center controllers and Traffic Management Units (TMUs) to change the flow of traffic to prevent future airspace overloads – which lead to high workload for controllers – and possibly limit unnecessary airspace and ground restrictions. There is a caveat that is important to note: analyzing predicted sector count vs. a truth data set fails to address the accuracy of how individual flights contribute to those counts. For example, an aircraft may be predicted to occupy a sector that it never actually enters. Another aircraft, *not* predicted to enter the sector does in fact enter it at around the same time the first aircraft was predicted to do so. The sector count prediction for this particular sector would have been correct, although two aircraft actually occupied unpredicted sectors.

The results of these analyses are presented as an aggregate of all flights and events over a certain prediction look ahead time horizon. Sector count is defined as the maximum instantaneous count over a fifteen minute time period. We are approximating this by looking at 15 consecutive one-minute bins and taking the maximum of those values. Then to get signed sector count error, we take predicted minus actual sector counts. To get absolute sector count error, we simply take the absolute value of this difference.

Figure 3 through **5** show the signed and absolute sector count prediction errors for ZAU and ZOB. The truth set for actual sector counts are taken from the ETMS track data. Contrary to the results shown in **Figure 3**, for active flights, we would expect smaller look ahead times to be associated with less prediction error. In dealing with proposed flights, however, we actually see smaller look ahead times to be associated with slightly higher demand errors. This is due to the way we compute sector count error for active flights. There is a heavy bias towards zero as the prediction look ahead time increases because there are so few active flights that are included in the statistics for large look ahead times. In order to understand this better, we created a plot based on percent error, as shown in **Figure 4**. By looking at the absolute percentage error graphs, we see that, in fact, active sector count error increases as look ahead time increases.

For active flights, ZAU exhibits slightly higher absolute sector count errors than ZOB. This can be largely attributed to ORD in ZAU. More last minute vectoring and circular holding in ZAU results in higher sector count errors. The opposite is true for proposed flights – ZOB shows more sector count errors than ZAU. This is likely due to the complexity of ZOB. ZOB handles many internal departures from airports such as Cleveland, Detroit, and Pittsburgh, as well as transcontinental traffic. This complexity leads to numerous traffic management initiatives are not taken into account in filed flight plans.

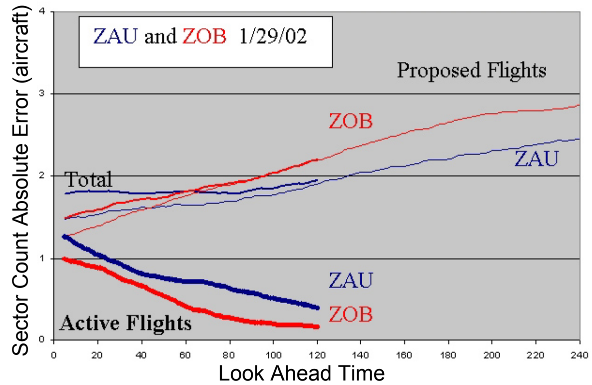

Figure 3. Absolute Sector Count Error for predictions of proposed and active flight for ZAU and ZOB on 1/29/02.

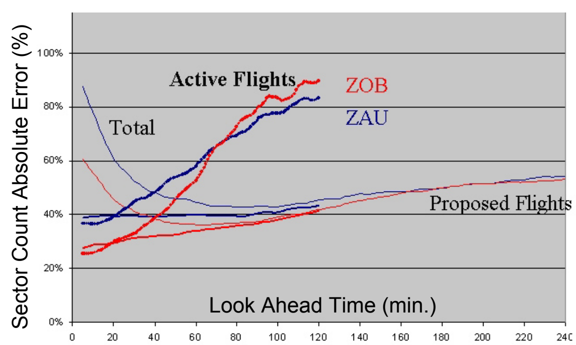

Figure 4. Percent Sector Count Error for predictions of proposed and active flight for ZAU and ZOB on 1/29/02.

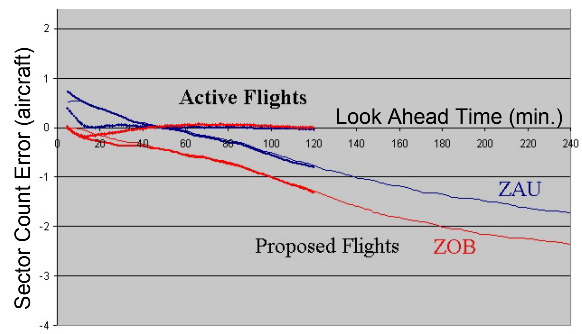

Figure 5. Signed Sector Count Error for predictions of proposed and active flight for ZAU and ZOB on 1/29/02.

The prediction of the sector demand is dominated by the aircraft that are on the ground when the prediction is made. Over 60% of the aircraft are on the ground when 30 minute look ahead time predictions are made, and when longer look ahead times are used, as with 120 minute and 240 minute look ahead times, the percentage of aircraft that are on the ground when the trajectory prediction is made is 98% or above. **Figure 6** illustrates the absolute sector count statistics for ZOB 48 over the time of day. These data indicate that the sector demand error is dominated by causes from aircraft on the ground prior to take off more than for errors associated with aircraft currently en route when trajectory predictions are made. Also, this is not heavily dependent on the time of the day. If the demand prediction is mostly in error due to errors in prediction take off times, then these plots indicate the degree to which the errors associated with predicting take off time will become a factor in the sector demand predictions.

Causes. There are several causes of sector entry time and sector count errors in **Figures 1-5**. These include:

- Aircraft sector entry times that are late due to path stretching or vectoring for conflict detection and resolution by ATC, as shown in **Figure 7**.

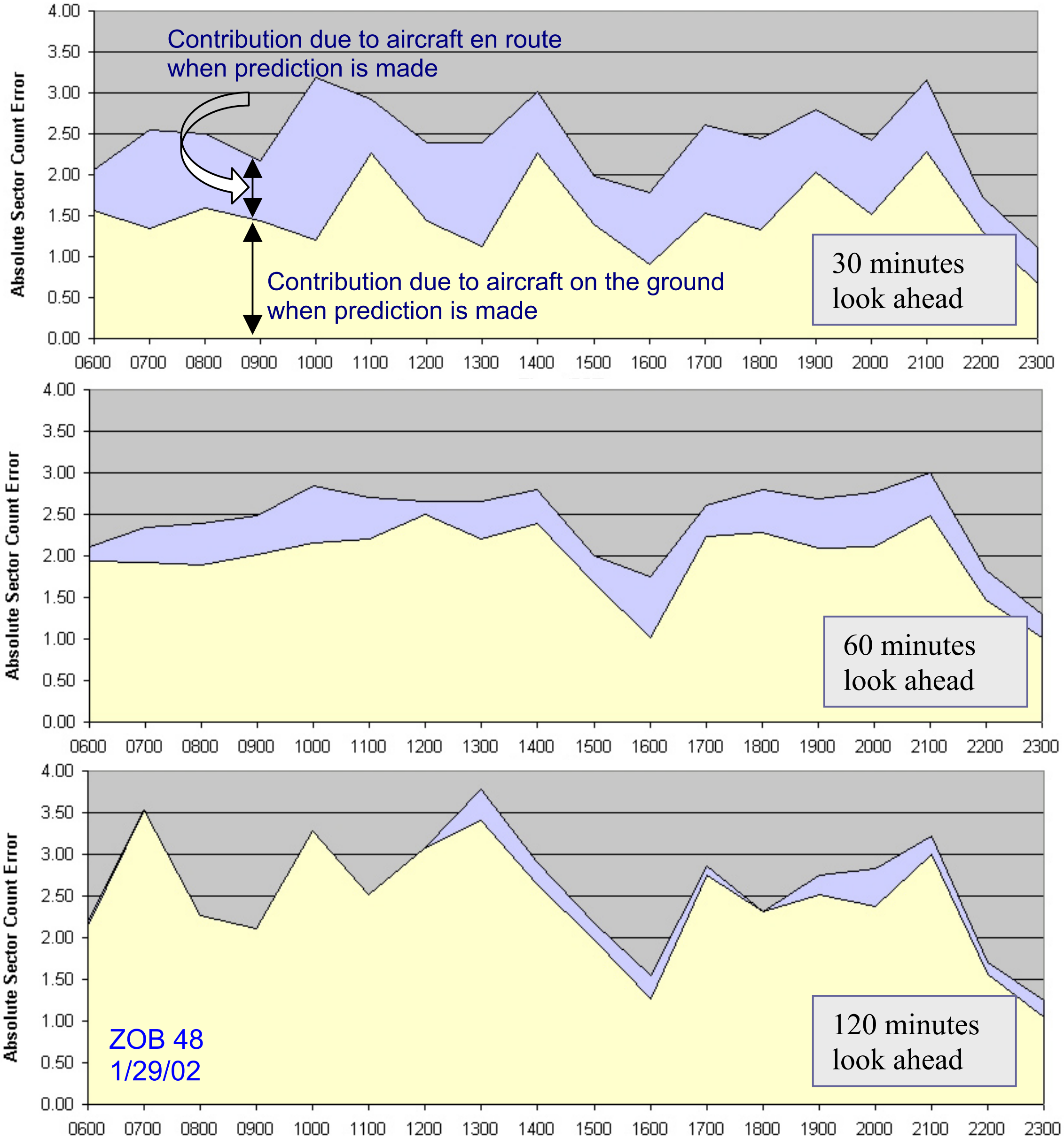

Figure 6. Sector Count error for on the ground vs. en route at different times of the day.

- Circular holding, as seen in **Figure 8,** can possibly cause multiple sector entries (but this is rare), and causes en-route delay that is not taken into account by FACET. This generally adds to the sector entry time error as FACET predicts the aircraft will proceed forward.
- Direct-to routes, as shown in **Figure 9**, result in aircraft flying shorter routes than the FACET predicts.
- Some flights have abnormal behavior that may be impossible to predict, as shown **Figure 10**.

These are events that are not revealed in the flight plan or a flight plan amendment, so the FACET trajectory predictor does not know about these events. Thus, the prediction that is based on the filed flight plan becomes in error.

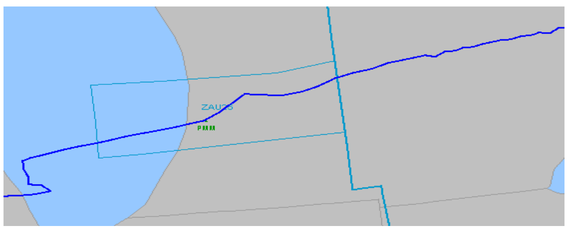

Figure 7. Vectoring is the most prevalent cause for sector entry time error in ZAU25.

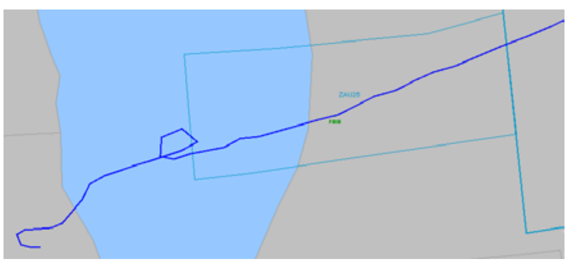

Figure 8. ORD circular holding causes sector entry time and sector count errors in ZAU25.

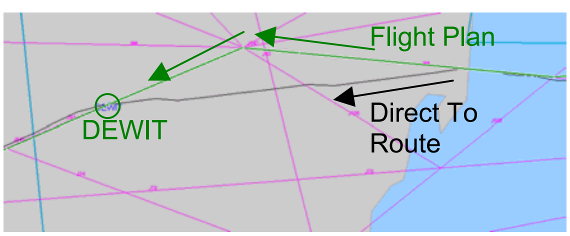

Figure 9. A Direct-to route (to DEWIT) actually reduces sector entry time.

Figure 10. An abnormal flight pattern causing errors in sector entry time and sector count.

Note also that signed sector count error graphs have a tendency to under-predict the actual sector counts. One reason we are under-predicting is because there are many GA and military pop-up flights that FACET has no way of knowing about because these aircraft don't submit a filed flight plan through ETMS. These pop-ups are in the 10-15% range. Currently, there is no good way to account for pop-up flights to improve the overall sector count error statistics.

Analysis of Departure Time Prediction Factors

Several factors contribute to departure time prediction errors.

Scheduled Take off Times. In terms of scheduled take off times, we analyzed both the accuracy of ETMS take off times, as well as the error in scheduled take off time.

The most accurate wheels off time measurement currently is ACARS Out, Off, On, In (OOOI) data. In order to understand the nature of the errors involved, an analysis of 20 large airports in the US was performed. On average, ETMS is about 1.1 min. late on its first data point that identifies when a takeoff has occurred. These data vary by airport based on the terrain, buildings, and the locations of radar. These results agree with the literature[9] showing that ETMS DZ times are typically 0–2 minutes after the actual wheels off time, and ETMS AZ times are typically between 1–4 minutes after the actual wheels on time.

Figure 11 illustrates the accuracy of the ETMS scheduled departure times relative to the OOOI wheels off times. These data illustrate the errors made when ETMS departure times are used to predict take off times and errors that exist in trajectory predictions that are made prior to take off. On average across 20 airports, there is about an 7.9 min. error. Once an aircraft takes off, the ETMS position data is fairly accurate, so these errors are immediately nullified. But prior to takeoff, these errors characterize the trajectory prediction error.

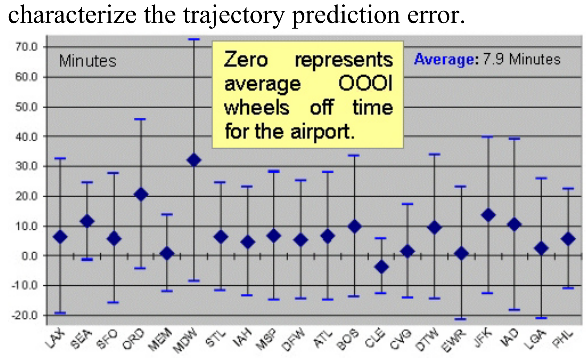

Figure 11. Error in the scheduled take off time based on OOOI wheels off time as truth data.

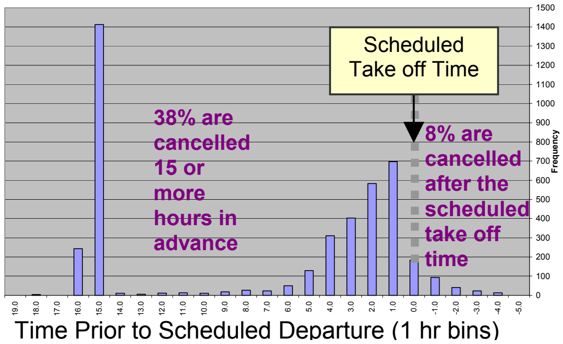

Figure 12. Cancellation times relative to the scheduled take off time based on ETMS data.

Cancellations. When analyzing the cancellations that occurred during the week of on-site observations at ZAU and ZOB, the majority of the airports had cancellation percentages between 3% and 10% for departures, with an average of 6.2%.

A flight is considered cancelled if the scheduled flight received a cancellation through ETMS RS message, RZ message, FX CDM message, or TO field in the Aggregate Demand List (ADL). An RS message is an internal ETMS message generated when a specialist takes an Original Airline Guide (OAG) flight out of the database. An RZ message indicates a flight was cancelled in a NAS flight plan. An FX message is the Collaborative Decision Making (CDM) message used by an airline to indicate that a flight is not operating. A flight is timed out by ETMS and receives a TO field in the ADL if it does not submit an activation message within 1 hour after the departure time for NAS or CDM cancelled messages. This time out period is 5 minutes if only OAG data has been received.

These cancelled flights do not include those flights that are "cancelled but flew". A "cancelled but flew" flight is a flight that received a cancellation message and still flew. This happens if a flight was cancelled but ETMS received an activation message within a certain time of the predicted departure time. An airline will issue cancellation messages when substituting flights during Ground Delay Programs (GDPs).

The effect of these cancellations on FACET prediction accuracy depends on the look-ahead time. The amount of look-ahead time determines the percentage of cancelled flights that are known to FACET at the time of prediction. If a prediction is made with a large look-ahead time, e.g., 4 hours, then flights that are cancelled after the prediction look-ahead time will be predicted to fly. This will directly contribute to an error in sector demand due to an inability to predict the cancellation.

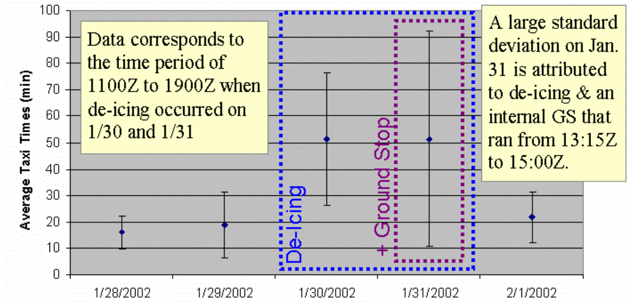

Figure 13. Effect of de-icing and a ground stop on the average taxi time at DTW.

Figure 12 displays the number of flights that are cancelled *x minutes* before departure, grouped in 1-hour bins. Two clusters of departure cancellations, one around 15 hours and one about 1.5 hours prior to departure. Although the airlines may submit cancellations days or even weeks before departure, Volpe does not synchronize the airline CDM data with ETMS data until 15 hours before departure time. This explains the large spike in the cancellation data at 15 hours prior to departure, which accounts for approximately 38% of the cancellations. These plots also show that flights are often cancelled at or after scheduled departure times. Cancelled flights, especially for long look ahead times, will be assumed to take off and included in the trajectory predictions and sector demand predictions. This cannot be avoided.

De-Icing. Next, we consider what happens during de-icing conditions at an airport, since this affects the error between the ETMS schedule take off time and the actual OOOI wheels off time. In our on-site observations at the ZOB center, we specifically saw a difference in the way Approval Requests (APREQs) were performed on days that had de-icing conditions compared to days where there was no de-icing. On de-icing days, aircraft were immediately released from CLE and DTW, presumably so that they would not have to de-ice twice and disrupt airport operations. As shown in **Figure 13**, the data for DTW airport reveals that the taxi times during the time period when de-icing was recorded is on average more than double the taxi time during days when there was no de-icing.

When de-icing operations are performed, the variance in the taxi time is greatly increased (most likely due to the amount of de-icing to be performed and the queue for de-icing). At DTW, a flight pushes back from the gate (starting the taxi timer) then travels to the "de-icing zone", gets de-iced, then proceeds to be inserted in the departure queue.

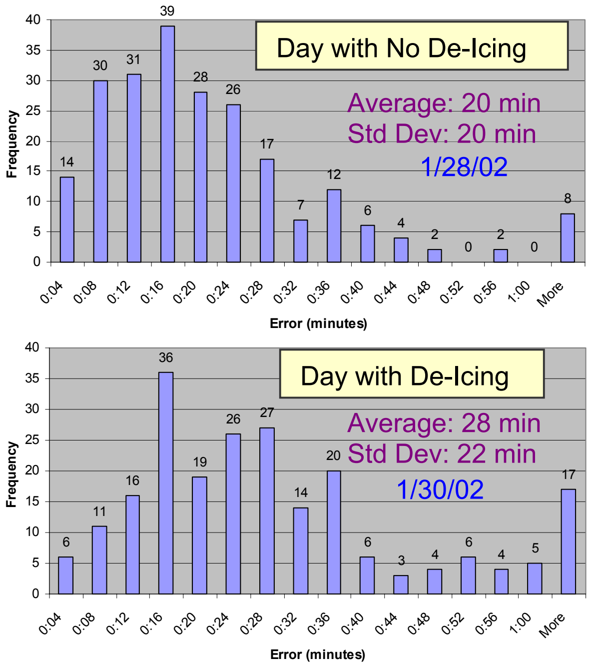

Figure 14. Error between OOOI wheels off time and the Scheduled ETMS Departure Time for DTW indicates a greater average error the day when de-icing occurs.

On days where there was no de-icing, the APREQs were used to hold aircraft until gaps opened up in the streams into ORD, for example. Thus, there will be a drastic difference in the taxi times and predicted departure times between these days. **Figure 14** shows that when this is taken in perspective with respect to the ETMS scheduled take off time, the de-icing seemingly causes the error to increase in time.

Analysis of TFM and ATC Factors

In order to generalize the aggregate statistics for TFM and ATC factors, we present data that represents the Miles-in-Trail Restrictions (MITs), Ground Stops (GS), and Ground Delay Programs (GDPs). These are data collected from the ATCSCC (Herndon, VA), and only include data that are recorded at the ATCSCC.

MIT Restrictions. NAS data for the dates that correspond to our on-site visits, as shown in **Figure 15,** illustrate how MIT restrictions were distributed geographically across the NAS for this time period. Clearly, there are portions of the NAS where there simply are very few MIT restrictions used, primarily in the Northwest. Also, the extreme Northeast (ZBW) and Southeast (ZJX and ZMA) used very few MIT restrictions. The most MIT restrictions are occurring in ZOB and ZNY centers.

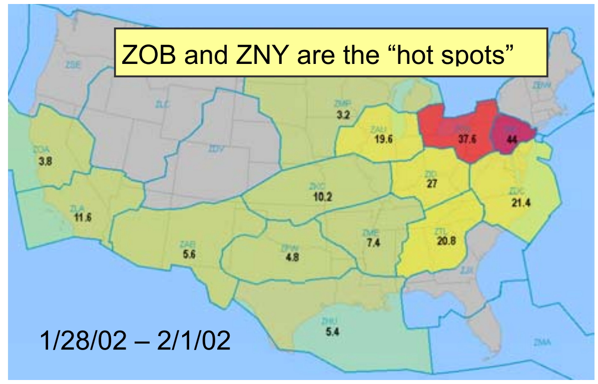

Figure 15. Average number of MIT restrictions per center (a center average < 1 is omitted).

Ground Stops. **Figure 16** shows the aggregate GS data across the NAS for the year 2001. The increase during the summer months is primarily resulting from the convective weather season. In September, a drop in the traffic volume across the NAS occurred after the September 11 tragedy, and thus, the number of GSs during the remainder of the year were low. Across the NAS, there were an average of 2.6 ground stops per day in 2001. The Northeast corridor exhibits a large portion of GS data, however, there is no one sector that seems to appear as one that uses GSs more than the others. The use of GSs seems to vary by day.

Ground Delay Programs. **Table 2** shows the aggregate GDP data across the NAS for the years 1998 through 2001. These data indicate an increase in the use of GDPs each year. There are certain airports for which GDPs are issued more than others. These airports are: ATL, BOS, EWR, LAX, LGA, ORD, and SFO.

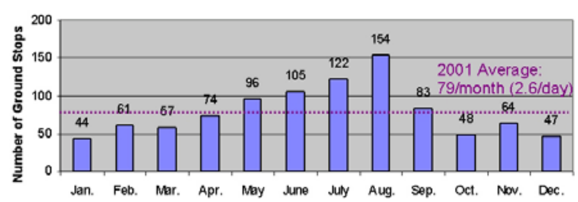

Figure 16. Ground stops per month in 2001.

Table 2. GDPs issued from 1998 to 2001.

Year	GDPs	Daily Average*
1998	513	1.4
1999	705	1.9
2000	1083	2.9
2001	799	2.8

*Note: The 2001 average is determined using Jan. – Aug. (243 days) data only.

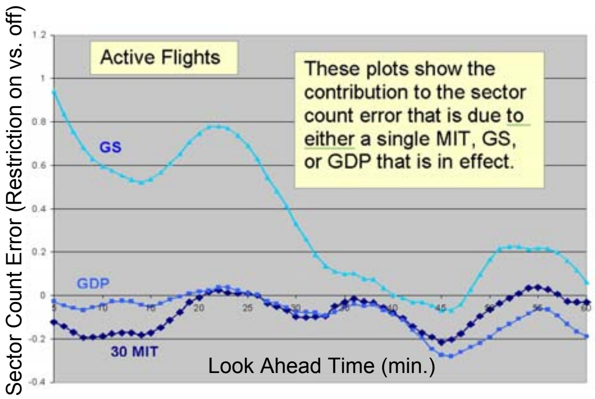

Figure 17. The net effect of MITs, GSs, and GDPs comparing time periods when the ATC restrictions were on to time periods when the ATC restrictions were off for active flights.

Effect of TFM and ATC Initiatives. In order to address the net affect that TFM and ATC initiatives (MITs, GSs, GDPs) cause on sector demand errors, we compare time periods when the ATC restrictions are in effect vs. time periods when there are no restrictions in effect. In terms of Eastern Standard Time (EST), our base line for no ATC restrictions is determined by data from 1/29/02 from 5:00 – 6:30 pm. The conditions of 30 MIT restrictions are for 1/29/02 from 6:30 – 8:30 pm, and GS data is from 1/28/02 from 12:00 – 1:00 am, and GDP conditions are for 1/30/02 from 6:30 – 8:30 pm.

Figure 17 illustrates a comparison between the effects of ATC restrictions on the sector count error for active flights. For MITs, a slight over prediction occurs with small look-ahead times but as the look ahead time gets larger, the affect on sector count error is small. First, the MIT restrictions that were in place were over OXI, and roughly 3.7% of all traffic in ZOB in a given day is involved with the jet route that passes over OXI. The number of flights that are actually subject to MIT restrictions is thus quite small, and the total sector count error was small as well. Also, MIT restrictions are used only as long as they are needed to solve a problem, so they are not used for long periods of time, and they do not seemingly affect the sector demand prediction results for long look ahead times. According to one controller, until MIT restrictions are above 30 to 40, there is not likely to be a noticeable difference in terms of sector demand error and how flights are handled.

Since a GDP occurs prior to take off and since our baseline data is en route data, the GDP results show insignificant effects when in comes to contributing significantly to errors in sector count. Most of the data for short look ahead times is far after take off, and only a few aircraft may still be on the ground due to a GDP (perhaps delayed because of other reasons like de-icing or taxi traffic). The effect of a GDP is showing up only slightly at long look ahead times, as seen in the figure.

The most significant contribution to sector count errors for active flights comes from ground stops (GSs). For a GS, results indicate under predicting for the majority of look ahead times, with the most pronounced effect occurring at short look ahead times. This may be due to upstream en route restrictions – airborne holding as in **Figure 18**. Recall that GSs are usually issued as a last resort due to adverse NAS conditions (e.g., congestion causing holding patterns or severe weather), so their effect is going to be immediate and they are typically used only for as long as they are needed.

Figure 18. A ground stop triggers upstream holding patterns.

In order to understand the relationship between an Expect Departure Clearance Time (EDCT) time submitted in a GDP and its potential to influence the predicted sector demand, the rules for when to send a EDCT message need to be reviewed:

1. *If no EDCTs have been sent yet, hold all EDCTs until 60 minutes before each departure.*
2. *If an EDCT has previously been sent, look to see if the new EDCT time is earlier or later than the previously sent one.*
   a. *If the new EDCT time is earlier than the existing EDCT, send it 60 minutes before the new EDCT time.*
   b. *If the new EDCT is after the existing EDCT, send the new time 30 minutes before the existing EDCT time.*

The algorithm used in the GDP for setting the EDCT time and reporting it as a flight plan amendment influences trajectory predictions for proposed flights. Under a GDP, the EDCT time is the most accurate estimate of the take off time, however, it is not reported until either 1:00 prior to take off or 30 minutes prior to take off, depending on the case described above. This is one possible explanation to why the sector count error peaks locally at 30 and 60 minute look ahead times for proposed flights, as shown in **Figure 19**.

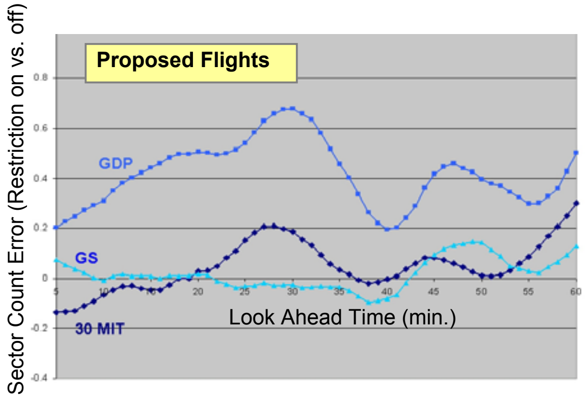

Figure 19. The net effect of MITs, GSs, and GDPs comparing time periods when the ATC restrictions were on to time periods when the ATC restrictions were off for proposed flights.

Circular Holding. Holding patterns are used for en route aircraft when sudden changes in the traffic flow inhibit aircraft from landing or from entering into centers (e.g., exiting ZOB into ZNY). Often, airborne holding is preceded by a GS or some other event, like a sudden change in MIT restrictions at a center boundary.

FACET does not have any information that an aircraft is in a holding pattern, so FACET will predict that an aircraft will fly through a sector without holding. The transit time is likely to be along the line of the average transit time, as shown in **Table 3**. Using a pattern recognition algorithm to detect holding patterns, we are able to identify the flights that experience circular holding (**Figure 20**) and separate them from the ones that do not. In doing so, we establish an average time for aircraft to pass west to east over J584 through SLT in ZOB77 (or the super high sector ZOB79 above ZOB77). The aircraft that experience circular holding remain within ZOB77 (ZOB79) a considerable amount of time above and beyond the average.

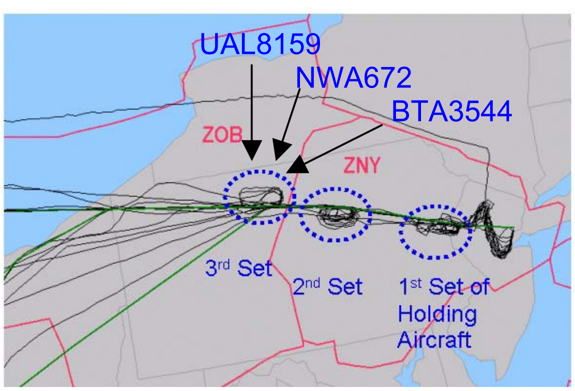

Figure 20. Circular holding that resulted from a ground stop in ZNY backs up into ZOB.

Table 3. Statistics for sector ZOB77 holding.

Aircraft	Circular Holding	Ave. Time (min.) in ZOB77	Percent over Average
Non-Hold Average	None	18	-
BTA 3544	1 Loop	30	67%
UAL 8159	1 Loop	29	61%
NWA 672	3 Loops	46	156%

Note that holding patterns not only cause an error in sector demand for the sector where the holding occurred, however, it also causes the prediction of where the aircraft will be in the future to be in error for all downstream locations. Once the holding pattern causes the delay, there is nothing in FACET that accounts for the delay for the rest of the flight. Thus, the error is going to remain with the aircraft for the rest of its flight unless a flight plan amendment is received.

SOPs and LOAs. Each center has its own Standard Operating Procedures (SOPs) and Letters of Agreement (LOA) with neighboring centers. These SOPs and LOAs can establish rules and restrictions that limit aircraft trajectories, thus, they affect trajectory predictions. Examples include:

- (SOP) The radar controller shall not assign or allow to be assigned a flight level to an aircraft that will operate within the sector that is lower than the lowest usable flight level.
- (LOA) No direct routes to ZNY at or below FL180.
- (LOA) All CLE arrival traffic must cross 20 DME east of the YNG VOR at FL240.

Individual LOAs may identify a specific altitude or location that an aircraft may be expected to cross a sector boundary. However, even though this may be used to modify trajectory predictions that greatly deviate from the LOA, such rules are very specific to individual jet routes and sectors. Coding of such rules is very difficult to generalize and may not have the pay off in comparison to the cost of coding such rules into a trajectory prediction algorithm such as FACET. Furthermore, LOAs often change, so there would be a requirement to monitor and update such changes.

TFM Actions due to Weather. Unfortunately, while there was weather present during our on site visits, the convective weather was very low, and we could not make any conclusions in this study due to the influence of convective weather on sector demand prediction accuracy. Air traffic controllers at the ZOB facility commented that most aircraft were going to easily climb over the weather that was present and the controllers did not have to make any special changes in their control actions for the day due to convective weather.

Discussion

ATCSCC Data Transfer. FACET does not have a reliable source of TFM control action data from the ATCSCC that is easily readable by computer automation. GS, GDP EDCT, and MIT restrictions data are potentially available in electronic format at the ATCSCC, and there is a benefit to having this data placed in a location where FACET can read the data in a well-defined format. The ATCSCC web site provides such data (**Figure 21**), but the format is not computer friendly and is based on communicating to a human user rather than for a computer system (e.g., FACET). If such a data connection is established in a well-defined format, then there may be benefit to trajectory predictions and sector demand predictions. This would also require that a model be built that accurately relates this data to predicted sector counts and sector entry times. The magnitude of such a benefit needs to be investigated in future research. MIT restriction data is currently being stored electronically through testing of the National Log Program. It remains to be seen whether this data is entered in a timely and consistent enough fashion to be of use for real time trajectory prediction. GS and GDP messages that get issued by the ATCSCC through the Traffic Situation Display (TSD) and the Flight Schedule Monitor (FSM) would allow FACET to have access to EDCT data that may improve predictions during GSs and GDPs.

ATCSCC Advisory

ATCSCC ADVZY 021 ORD/ZAU 01/28/2002 CDM GROUND DELAY PROGRAM

MESSAGE:
```
AIRPORT: ORD
ADL TIME: 14:55Z
PROGRAM TYPE: RBS PP
ARRIVALS ESTIMATED FOR: 281800Z - 290059Z
PROGRAM AAR: 78
ALL CENTERS ARE INCLUDED IN THE PROGRAM.
THE FOLLOWING SHALL APPLY
FA DELAYS:
All
EXEMPTED AIRPORTS: NONE
MAXIMUM DELAY: 83
AVERAGE DELAY: 33
REASON: WEATHER, LO CIGS/REDUCED AAR
REMARKS:
```

EFFECTIVE TIME: 281458 - 290159

SIGNATURE: 02/01/28 14:59 FSB.//wkstn13a 703-708-5113

Figure 21. A GDP Advisory from the ATCSCC web site.

Airport Surface Movement Data. In the future, there may be a source for ACARS on times, pushback times, or estimated take off times that are based on taxi surveillance data available to FACET. If so, then there is a possibility that the pushback time and the average taxi time could be used to predict the take off time. Additionally, historical data could assist in such a prediction. Surface Management System[2] (SMS) taxi and take off time predictions may also determine a good estimate for take off time. Such a prediction for the takeoff time of an aircraft may prove to be a better estimate than the filed flight plan take off time, however, future research should be performed to build an appropriate model and to verify this proposition.

Parking Gate Information. There is long term potential to use parking gate information in the ETMS data feed to improve departure time predictions. It is currently very difficult to obtain information about the 'line of flight' of an aircraft. This line of flight refers to the sequence of an airline's flights that are conducted using a specific aircraft. Knowledge of the line of flight would allow systems to more accurately predict the departure time of an outbound flight. If the inbound flight of the aircraft that will make up an outbound flight is late, then it is reasonable to predict that the outbound flight will depart late, unless there is slack in the scheduled turn-around time for the aircraft.

One way by which the line of flight information could be inferred and predictions of departure times improved is by inclusion of the parking gate in the ETMS data feed. The aircraft used for the arrival flight assigned to a parking gate will likely also be the aircraft used for the next departure flight assigned to that parking gate. With this information, the departure time of the departure flight can be estimated based on the arrival time of the arrival flight at the same parking gate. Line of flight information would greatly benefit long-term trajectory predictions and long term sector demand predictions. Without such information, long-term predictions are currently limited.

Note that airlines have many operational options available to them to deal with situations in which arrival flights are late. A different aircraft may be assigned to the departure flight if the arrival flight is late. Other parking gate changes required by maintenance or other factors may also reduce the accuracy of the line of flight data derived from parking gate information. Ultimately, parking gate information would potentially allow predictions of take off times to be done prior to the filed flight plan and are likely have better accuracy than the OAG scheduled take off time. This would need to be investigated in a future effort to establish the value of such information.

Conclusions

Based on on-site observations and data from Cleveland and Chicago Centers in January, 2002, the single most important factor affecting sector demand prediction errors is related to predicting the take off time of aircraft. The second most significant factor is from the prediction of TFM and ATC control actions and how they affect en route traffic. Predicting take off times is complicated by the lack of data about take off times allocated in ground delay programs (although the ATCSCC posts these on a web site, they are not in a format that is readable by computer automation). Furthermore, de-icing conditions greatly affect take off times, and de-icing conditions are also not released in a format that is easily read by computer automation. Also, although cancellations are known, they may not be known at the time of prediction for large prediction look ahead times. For en route aircraft, predicting future motion is most complicated by holding patterns, which often result from ground stops. These too are events that are not known to the sector demand prediction algorithm. Miles-in-Trail restrictions did not appear to affect sector demand predictions as much as ground stops and ground delay programs, most likely because they only affect aircraft on certain routes where the restrictions are in effect. In the future, information about ground stops, de-icing conditions, ground delay program EDCT times, and holding patterns are needed in a format that can be read by computer automation so that more accurate trajectory predictions can be made and more accurate sector demand predictions can result.

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