AIAA Guidance, Navigation and Control Conference and Exhibit
20 - 23 August 2007, Hilton Head, South Carolina

AIAA 2007-6450

A New Model to Improve Aggregate Air Traffic Demand Predictions

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[Abstract] Federal Aviation Administration (FAA) air traffic flow management (TFM) decision-making is based primarily on a comparison of predictions of traffic demand and available capacity at various National Airspace System (NAS) elements such as airports, fixes and en-route sectors. The FAA uses the Enhanced Traffic Management System (ETMS) to predict traffic demand and available capacity, identify congestion and alert NAS elements when the predicted demand exceeds capacity. Although predicted demands and capacities are uncertain, ETMS treats them deterministically and does not take into account the errors in subsequent prediction updates. This paper proposes a regression model for improving aggregate traffic demand predictions in ETMS. This approach acknowledges the uncertainty in these predictions, and uses ETMS demand count data in a novel way to make improved predictions in terms of both accuracy and stability. The proposed linear regression model includes predicted demand counts for a time interval of interest along with the demand predictions for two immediately adjacent intervals: the preceding and the following ones. The model was calibrated and validated using data from 9 airports and 13 en-route sectors. Numerical results are presented that illustrate the potential benefits of using the proposed model.

I. Introduction

Traffic Flow Management/Air Traffic Control (TFM/ATC) decision-making is mainly based on a comparison of predicted traffic demand and available capacity at various National Airspace System (NAS) elements such as airports, fixes and en-route sectors. This comparison helps a TFM specialist identify a potential congestion problem and its severity when predicted demand exceeds capacity of a NAS element. Demand is measured in aggregate number of aircraft per a specific time interval. The Enhanced Traffic Management System (ETMS) considers traffic demand per 15-minutes and relates it to 15-minute capacity. If predicted demand exceeds capacity, it raises an alert. The aggregate demand count predictions are performed by predicting events for individual flights along the origin-destination routes (time and location) and then aggregating all the flights for a specific location and time interval. The demand counts are updated when new flight data become available. Although the predictions are not 100% accurate, and predicted aggregate demand fluctuates with each update, ETMS does not consider this uncertainty and treats the predictions deterministically. Acknowledgement of the existence of uncertainty and random errors in the demand predictions requires the application of statistical methods to improve the accuracy and, hence, reduce the uncertainty in predictions. This would improve the ETMS prediction capabilities and TFM decision-making procedures. This would also enable more reliable probabilistic demand forecast and probabilistic TFM decision-making.

Probabilistic TFM is a new direction that takes into account uncertainty in predictions of traffic demand and capacity to provide the TFM specialists with better decision support in the uncertain environment. The concepts of probabilistic TFM and proposals for its application can be found in recent publications (see, for example, Zobell et al [1], Wanke et al [2], which also provide extensive references on this subject). The probabilistic approach generally characterizes errors in demand and capacity predictions, determines the probability distributions of the errors and then uses the distributions to determine the probabilities of congestion of NAS elements. This would give a TFM specialist the information on the likelihood and severity of congestion that would help to find the best way to resolve

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a congestion issue. Probabilistic TFM deals with the given level of uncertainty in predictions leaving the subject of improving the accuracy of the predictions as a separate issue. Improving the accuracy of predictions is fundamental for air traffic flow management and would affect various aspects of TFM. It is important for improving current TFM decision-making and would definitely benefit and compliment probabilistic TFM.

There are many factors causing uncertainty in predictions of aggregate traffic demand. They are mostly associated with errors in predictions of flight events for individual flights. The FAA and aviation community, through the Collaborative Decision Making (CDM) program, achieved significant improvements in data quality in terms of accuracy of prediction of flight events. However, the predictions are still not perfect and this imperfection can be taken into account for further improvement of accuracy of aggregate demand predictions through statistical and probabilistic methods. There is a growing interest to this direction, and, although little has been published, the preliminary research results look promising.

A constructive approach to the probabilistic prediction of air traffic demand has been proposed in Meyn [3]. Based on probability density function of errors in predictions of estimated time of arrival (ETA) for individual flight at an airport or en route sector, the author calculates probability distribution of predicted aggregate traffic demand for a specific time interval and selects an expected or the most likely value as a predicted demand. To estimate the benefits of probabilistic demand predictions over deterministic ones, the author used both an analytical method and Monte Carlo simulation. The analysis was conducted on artificial data (not actual air traffic data) and showed that the probabilistic approach over-performed the deterministic one in terms of accuracy of demand prediction. In particular, a probabilistic demand prediction provided 15% - 20% reduction in the standard deviation of errors relatively to deterministic predictions.

This paper presents a different approach to improving the accuracy of aggregate demand predictions in ETMS that takes into account their stochastic nature. The approach is based on direct processing of current ETMS deterministic aggregate demand predictions without explicit usage of predictions for individual flights. A linear regression model is proposed for estimation of traffic demand predictions for a specific time interval. The model comprises a linear combination of the deterministic demand predictions for an interval of interest and the ones for two immediately adjacent preceding and following intervals. The predictions for adjacent intervals provide a mechanism to transfer uncertainty in flight ETA into uncertainty in aggregate demand, without having to explicitly consider the predictions for individual flights. The quality of the model was analyzed on historical ETMS data. The regression model provided a reduction of standard deviation of demand prediction errors practically of the same magnitude as reported in Meyn [3] but the effect was achieved by a simpler prediction algorithm.

High accuracy and stability of traffic demand predictions play an especially important role in predicting congestion and its severity when traffic management initiatives, such as ground delay programs (GDP) or miles in trail (MIT), are contemplated. Inaccurate predictions may be costly because

- Over-predicted demands may lead to excessively conservative strategies by over-controlling traffic with the possibility of excessive or unnecessary ground delays
- Under-predicted demands may lead to excessively aggressive strategies that under-control traffic with the possibility of excessive airborne delays
- The bad predictions may lead to the loss of valuable arrival slots during CDM GDP slot allocation procedures
- Instability of traffic demand predictions may cause frequent “flickering” of alerts during consecutive traffic updates (i.e., alerts being turned on and off frequently). This reduces the credibility of the system, and may lead to unnecessary TFM actions.

This paper is focused on reducing uncertainty in traffic demand predictions caused by the errors inherent in ETMS itself, such as the errors in estimated times of flight arrivals at the NAS element, and not by the impacts of TFM actions such as ground delay programs, rerouting or miles-in-trail. Therefore the historical ETMS data used in the study was collected for quiet days without a large number of traffic management initiatives.

This paper reports on some results of analysis of the accuracy of ETMS demand predictions and presents a regression model that uses ETMS prediction data in a novel way to improve traffic demand predictions in terms of both accuracy and stability. The main feature of the regression model is that it represents a linear combination of demand counts predicted for a time interval of interest and the demand predictions for the adjacent preceding and following intervals.

The motivation for using predictions for adjacent intervals is a possibility of migration of estimated time of a flight arrival from one 15-minute interval to another during consecutive updates. As a result, a flight can contribute to aggregate counts in different 15-minute intervals during consecutive demand updates. For example, if at 14:00 a flight is predicted to arrive at an airport at 17:58, it will contribute one flight to the prediction of aggregate demand for the 17:45 – 17:59 interval. During the next update of flight arrival time performed at 14:05, this flight is predicted to arrive at 18:03, thus contributing one flight to the aggregate demand prediction for an adjacent, 18:00 – 18:14, interval. Furthermore, there is a likelihood that some of the flights predicted at 14:00 to arrive in the 18:00 – 18:14 interval, at the next update at 14:05 would be predicted to arrive in the 17:45 – 17:59 interval. To generalize, if the random errors in predictions of time of flight arrival at a NAS element put the flight to an earlier or later 15-minute interval during consecutive flight updates, it is possible that the predicted counts for those adjacent intervals will provide useful information for improving the prediction for the current interval.

A new regression model was developed that considered the predicted counts for these adjacent intervals. It was calibrated for nine airports and thirteen en route sectors using data from the summer of 2005 and the winter and spring of 2006. The model was then validated using 7 days of data (from the summer of 2005 and the winter of 2006) that were not in the original calibration set. It has been shown that this model provides improved accuracy and stability over the current deterministic model.

The remainder of this paper is in the following sections:

- Section II presents the results of analysis of current ETMS demand predictions.
- Section III describes the development and calibration of the new regression model.
- Section IV describes the validation of the regression model.
- Section V presents conclusions.

II. Current ETMS Traffic Demand Predictions

This section describes the results of analysis of the quality of current ETMS predictions of the number of flights in a 15-minute interval. This analysis was performed on selected airports and sectors for 19 days of data from January 2006, and for 15 days in April and May 2006. The results for the three months were similar. Therefore, this section presents only the January analysis.

For airports, the data includes the number of arrivals in a 15-minute interval. For sectors, the data includes the peak number of flights within a one-minute bucket of a 15-minute interval. ETMS predicts both of these quantities.

Figure 1 illustrates the distribution of errors in 15-minute traffic demand predictions at ATL airport for various look-ahead times (LAT). The mean error is close to zero and standard deviation is increasing with increasing LAT. The curve for LAT < 1 hour has a standard deviation of 4.5 flights, while the curve for LAT > 2 hours has a standard deviation of 6 flights (see Fig.2 for ATL).

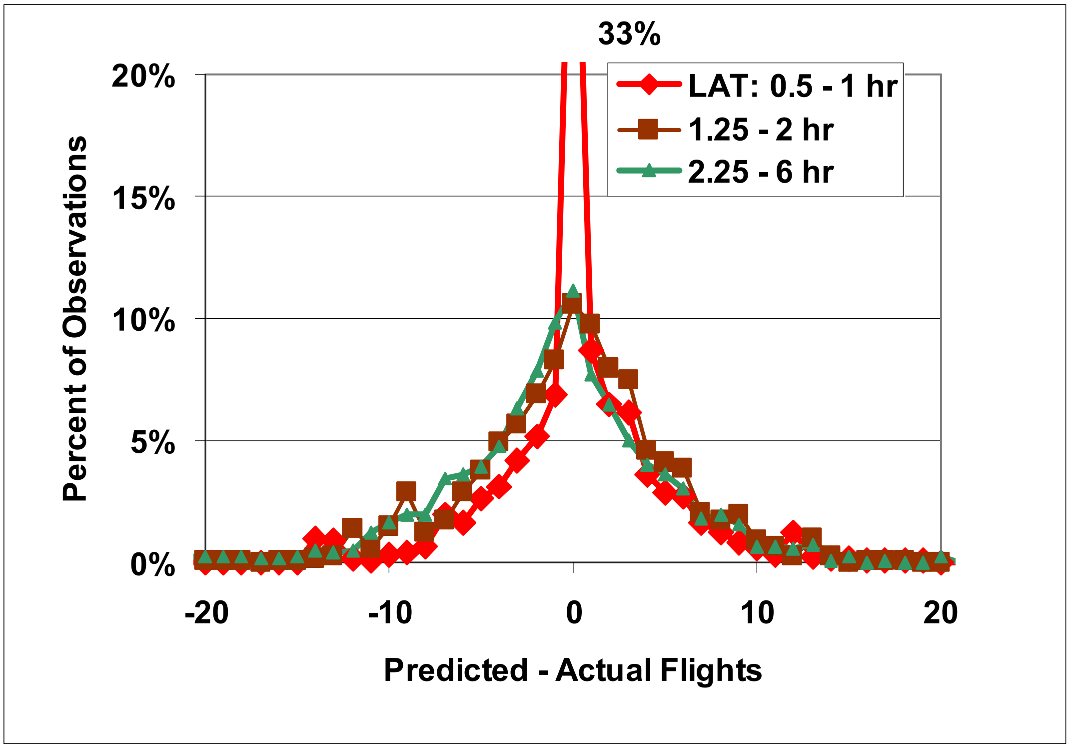

Figure 1. Histogram of Prediction Errors for ATL, January Data

Rather than showing separate histograms of the error for every airport and sector, Figures 2 and 3 display the standard deviation of errors of demand predictions for various LAT at selected airports and sectors, respectively.

The numbers on the X-axis (along the bottom of each chart) represent the average number of arrivals in 15 minutes for airports, and the average number of peak flights during 15 minutes for the sectors. For both airports and sectors, longer look-ahead times are associated with a larger standard deviation. The busier airports (e.g., ORD, ATL) also have a larger standard deviation.

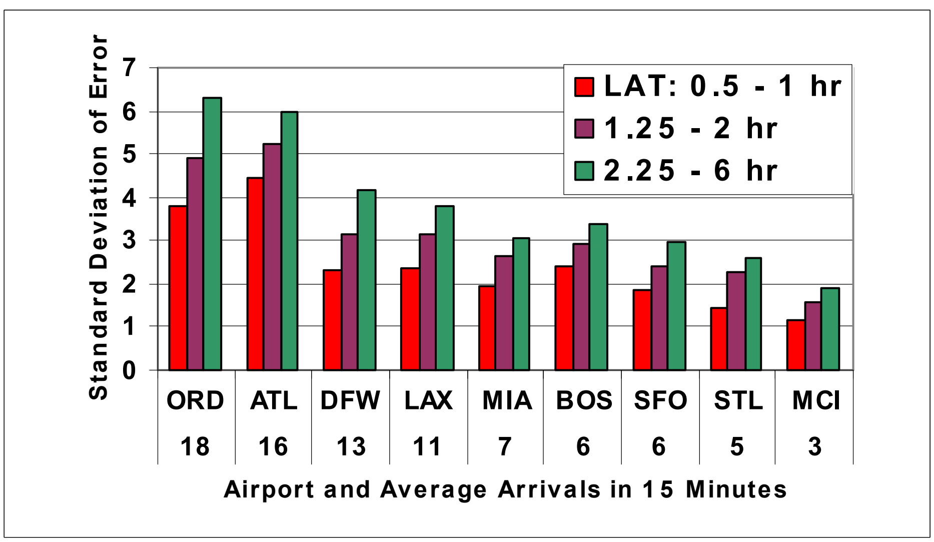

Figure 2. Standard Deviation of Error for Airports- January 2006

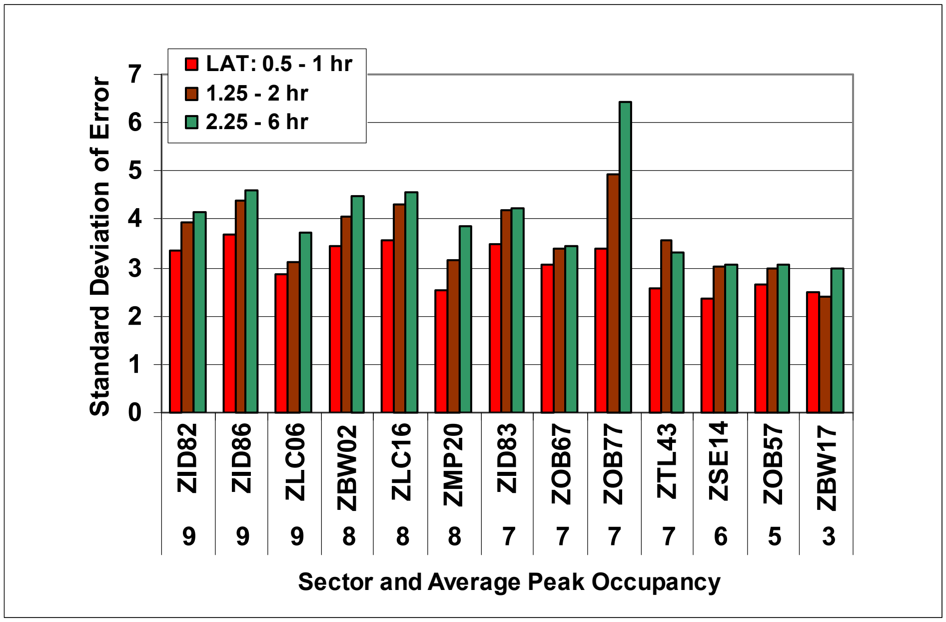

Figure 3. Standard Deviation of Error: Sectors- January 2006

III. Regression Model Development

Preliminary results of analysis of several regression models for improving the accuracy of aggregate demand predictions are presented in Smith and Gilbo [4]. These models included factors such as

- Adjacent intervals. Both the immediately adjacent (15 minute preceding and following) and the next (30 minute preceding and following) intervals were considered.
- Airport-specific coefficients.
- Active and proposed flights.

The analysis showed that including predictions for more distant (30-minute) adjacent intervals did not make much difference, and the model that includes demand predictions in two immediate adjacent intervals gave the best combination of improved results and simplicity. Therefore, the following regression model has been selected and is analyzed in this paper:

(1) $\hat{A}(t,n) = aF(t\text{-}15,n) + bF(t,n) + cF(t+15,n) + k = A(t) + \varepsilon(t,n),$

where

$\hat{A}(t,n)$ - Predicted demand for the interval *t,*

F(t,n) - ETMS demand prediction for interval *t*

F(t-15,n) and *F(t+15,n)* – ETMS demand predictions for the preceding and the following 15-minute intervals relative to interval t, respectively.

a, b, c, and *k* are coefficients to be determined. (Using this notation, the current ETMS deterministic model has $b = 1$ and $a = c = k = 0$.)

A(t) – actual number of flights at interval *t.*

Model (1) was calibrated for several data sets and look-ahead times (Table 1). Each data set combined data from all nine airports.

Table 1 Airport Model: Coefficients for Various Look-ahead Times

	Look-ahead (hours)	< 1	< 1	1-2	1 –2	2- 3	3 – 4	4 – 6
	Data (6/2005 or 1/2006)	6/05	1/06	6/05	1/06	1/06	1/06	1/06
	Root Mean Square Error	2.83	2.60	3.12	2.90	3.30	3.44	3.69
	R-squared[‡]	0.87	0.87	0.85	0.85	0.79	0.77	0.74
Constant	**Coefficient k**	**-0.50**	**-0.127**	**-0.20**	**0.01**	**0.300**	**0.678**	**1.168**
	Standard Error	0.09	0.024	0.1	0.024	0.028	0.030	0.027
F(t-15,n)	**Coefficient a**	**0.27**	**0.231**	**0.31**	**0.302**	**0.309**	**0.289**	**0.275**
	Standard Error	0.011	0.003	0.011	0.003	0.004	0.004	0.004
F(t,n)	**Coefficient b**	**0.61**	**0.585**	**0.54**	**0.532**	**0.467**	**0.445**	**0.413**
	Standard Error	0.011	0.003	0.012	0.003	0.004	0.004	0.004
F(t+15,n)	**Coefficient c**	**0.21**	**0.228**	**0.20**	**0.204**	**0.249**	**0.276**	**0.277**
	Standard Error	0.011	0.003	0.011	0.003	0.004	0.004	0.004

For the 0 – 2 hour look-ahead times, further calibration was performed with data sets from the following time ranges:

- June 21-25, 2005
- June 21-25 and July 13-17, 2005
- January 1 – 19, 2006
- April 10 – 16, 2006 and
- May 5 – 12, 2006.

The coefficients did not vary much for the various data sets, and all of the constant terms were fairly close to zero (Table 2).

Table 2 Airport Model: Regression Coefficients

		LAT < 1 hr					LAT 1- 2 hr				
		June 2005	Jun/Jul 2005	Jan. 2006	Apr. 2006	May 2006	June 2005	Jun/Jul 2005	Jan. 2006	Apr. 2006	May 2006
Constant	**k**	-0.50	-0.42	-0.13	0.10	0.33	-0.20	0.34	0.01	0.22	0.89
F(t-15,n)	**a**	0.27	0.25	0.23	0.20	0.23	0.31	0.31	0.30	0.23	0.25
F(t,n)	**b**	0.61	0.61	0.58	0.62	0.57	0.54	0.51	0.53	0.53	0.46
F(t+15,n)	**c**	0.21	0.18	0.23	0.15	0.14	0.20	0.16	0.20	0.22	0.17

In the above tables, among the regression coefficients, coefficient **b** is consistently the largest and coefficient **c** is consistently the smallest. This means that the predicted demand counts at the 15-minute interval of interest (F(t, n) component) have the highest weight (coefficient **b**) in the regression model, while the demand counts at the preceding and the following 15-minute intervals (F(t-15, n) and F(t+15, n) components, respectively) have smaller weights. Additionally, coefficient **a** is consistently greater than coefficient **c**. In other words, the preceding counts F(t-15, n) contribute to the regression with a higher weight than the following counts F(t+15, n). The latter is not surprising, since flights are more often late than early. The regression coefficients tended to change with increasing look-ahead time. In particular, coefficient **b** became smaller and coefficients **a** and **c** became larger for the longer look-ahead time.

When compared with current ETMS deterministic predictions, the standard deviation of errors in predicted demand decreased by 14% - 16% for all look-ahead times ranging from 30 minutes to 6 hours

A similar regression analysis was performed for sectors, where traffic demand is measured by the peak number of flights within a one-minute bucket of a 15-minute interval. Table 3 shows the computed coefficients for this model.

[‡] R-squared is a standard measure of the quality of a regression. It ranges between 0 and 1, with 1 reflecting a perfect correlation between actual and predicted values, and 0 reflecting no correlation.

Again, coefficients were as expected, with **b** being the largest, and the value of **b** decreased as look-ahead times increased. However, the constant term was substantially larger for the sector model, especially for longer look-ahead times.

For en route sectors, the standard deviation of prediction errors also decreased when compared to current ETMS predictions. The decrease was higher for a longer look-ahead time. In particular, for LAT between 30 minutes and one hour, the standard deviation decreased by 11%; for LAT between 1 and 2 hours – by 14%; for LAT between 2 and 6 hours – by 16%.

Table 3 Sector Model: Coefficients for Various Look-ahead Times

	Look-ahead (hours)	**<1**	**< 1**	**1-2**	**1 –2**	**2- 3**	**3 – 4**	**4 – 5**	**5 – 6**
	Data (6/2005 or 1/2006)	6/05	1/06	6/05	1/06	1/06	1/06	1/06	1/06
	Root Mean Square Error	3.43	2.86	3.86	3.34	3.62	3.71	3.77	3.84
	R-squared	0.67	0.59	0.59	0.44	0.34	0.30	0.29	0.26
Constant	**Coefficient k**	**1.64**	**0.832**	**2.94**	**2.127**	**3.261**	**3.748**	**3.888**	**4.193**
	Standard Error	0.10	0.027	0.18	0.028	0.029	0.029	0.030	0.043
F(t-15,n)	**Coefficient a**	**0.26**	**0.280**	**0.18**	**0.233**	**0.203**	**0.188**	**0.201**	**0.198**
	Standard Error	0.014	0.005	0.014	0.005	0.005	0.006	0.006	0.012
F(t,n)	**Coefficient b**	**0.48**	**0.408**	**0.42**	**0.297**	**0.245**	**0.225**	**0.208**	**0.212**
	Standard Error	0.018	0.006	0.019	0.006	0.007	0.008	0.008	0.009
F(t+15,n)	**Coefficient c**	**0.011**	**0.139**	**0.14**	**0.145**	**0.139**	**0.156**	**0.160**	**0.103**
	Standard Error	0.014	0.005	0.015	0.005	0.005	0.006	0.006	0.009

IV. Model Validation

The accuracy and volatility of predictions from the new regression model were tested using 7 days of data that were not in the calibration set. The data included some 27,000 predictions for various airport, time of prediction (n), and event time (t) combinations, and some 33,000 predictions for various sector, time of prediction (n), and event time (t) combinations. The days included three days in July 2005 (Friday July 22, Saturday July 23, Wednesday July 27) and four days in February 2006 (Tuesday February 14 – Friday February 17). This section presents three sets of validation results:

- Airport demand prediction accuracy
- Sector demand prediction accuracy
- Airport demand prediction stability

A. Airport Demand Prediction Accuracy

The following airport model was used for validation:

(1) $\hat{A}(t,n) = \mathbf{0.25}F(t\text{-}15,n) + \mathbf{0.55}F(t,n) + \mathbf{0.2}F(t+15,n)$

These regression coefficients were chosen as typical of those observed in the model calibration (see Tables 1 and 2).

The figure of merit used was the standard deviation of prediction error ($\hat{A}(t,n)$-$A(t)$).

Figure 4 shows the results for each airport with look-ahead times ranging from 30 minutes to 2 hours. The new model showed the same or improved accuracy over ETMS for all airports. The improvement averaged 12 percent, and ranged between 2 and 20 percent, depending on the airport.

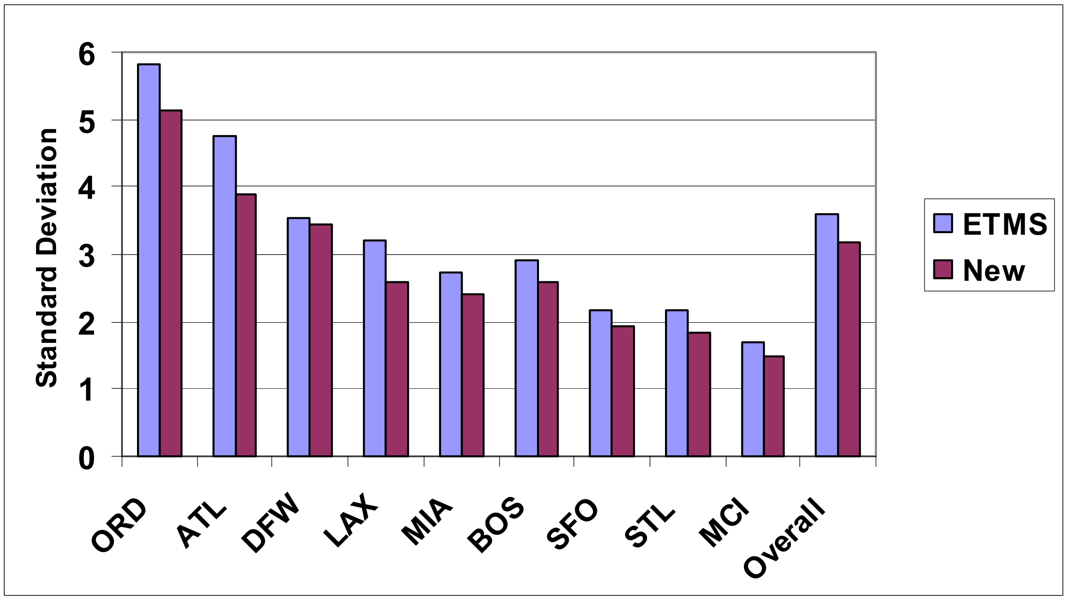

Figure 4 Airport Model Validation Results

B. Sector Demand Prediction Accuracy

Recall that for the sector regressions, the constant term was higher for longer look-ahead time (see Table 3). Accordingly, a model was developed where the coefficients depend on the look-ahead time. The coefficients are shown in Table 4.

Table 4 Sector Model Coefficients

LAT	Constant	F(t-15,n)	F(t,n)	F(t+15,n)
0:30	0.461	0.252	0.444	0.143
0:45	0.833	0.252	0.411	0.143
1:00	1.205	0.252	0.379	0.143
1:15	1.577	0.252	0.346	0.143
1:30	1.949	0.252	0.314	0.143
1:45	2.321	0.252	0.281	0.143
2:00	2.693	0.252	0.249	0.143

The new model showed the same or improved accuracy over ETMS for all sectors (see Figure 5). The improvement averaged 12 percent, and ranged between 0 and 22 percent.

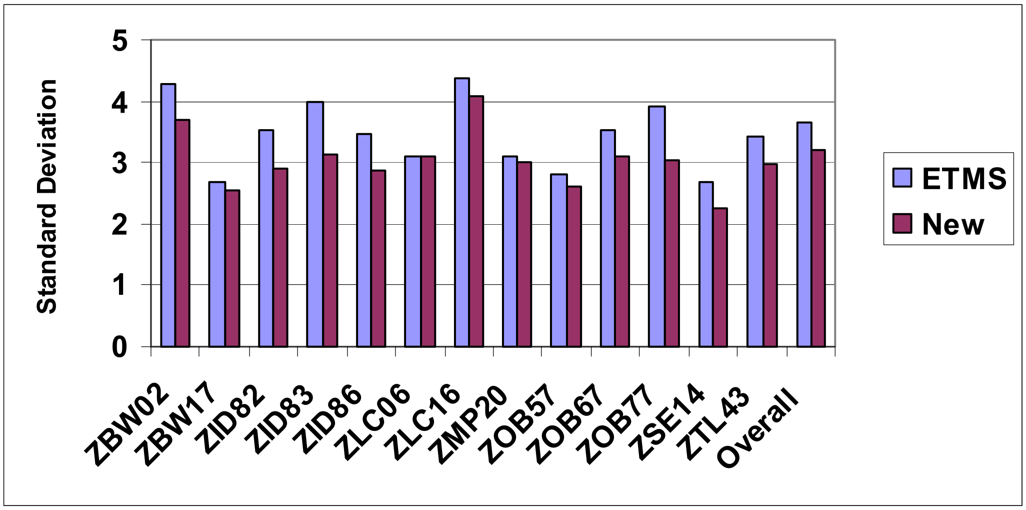

Figure 5. Sector Model Validation Results

C. Airport Demand Prediction Stability

In addition to being accurate, it is also desirable that demand predictions be stable. Stability means that the prediction does not change much during consecutive demand updates. With improved accuracy, one can expect a reduced range of variation in successive predictions, and thus, improved stability.

For traffic flow managers, unstable predictions can manifest themselves as frequent changes in alert status ("flickering"), where Monitor/Alert switches on and off as the prediction crosses the capacity threshold. The problem is most evident when demand is near capacity. When demand remains far below capacity, there might be no alert, even though the volatility of that demand may be reduced. Similarly, if demand is far above capacity, there is always an alert. In this study, we had focused on non-congested days, with demand usually less than the airport capacity (alert thresholds) represented in ETMS.

In order to create a more meaningful comparison between ETMS and the new regression model with respect to stability of traffic demand predictions, an artificial alert threshold equal to the average number of flights in a 15-minute interval for each airport was created (recall the numbers along the x-axis in Figure 2). Two measures were then examined:

- The total number of times the demand prediction exceeds the threshold. There were a total of 3,032 observations for each airport. If the demand exceeds the threshold one half of the time, this value would be approximately 1,500.
- The number of changes in alert status. This is the number of times the demand prediction crosses the capacity threshold. A lower value is better.

Table 5 and Figure 6 show the results.

Table 5 Airport Stability Results

Airport	Threshold	Number of observations where demand exceeds the threshold		Number of changes in alert status	
		ETMS	New	ETMS	New
ORD	18	1569	1726	397	258
ATL	16	2045	2201	231	124
DFW	13	1676	1925	298	177
LAX	11	1720	1929	369	237
MIA	7	1621	1798	297	179
BOS	6	1763	1942	412	231
SFO	6	1606	1769	355	183
STL	5	1564	1717	365	218
MCI	3	1445	1585	412	231
Grand Total		15009	16592	3136	1838

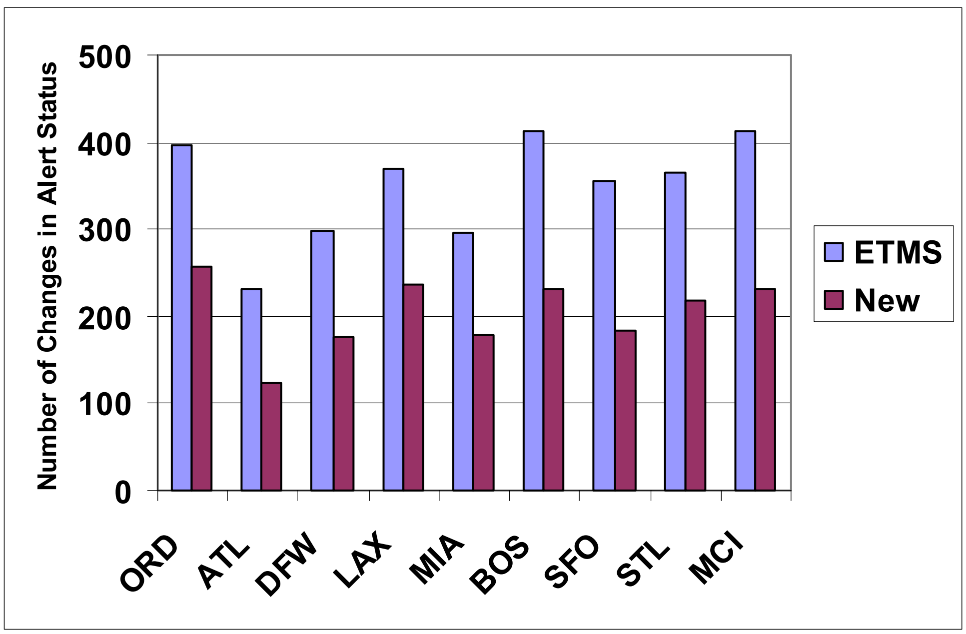

Figure 6. Airport Stability Results

For both the ETMS and new models, there were a substantial number of instances where predicted demand exceeded the artificial threshold. However, the number of crossings of this threshold has been reduced by between 35 and 48%, depending on the airport.

V. Conclusions

ETMS currently makes its aggregate traffic demand predictions based on deterministic projections of traffic and neglects random errors in predictions. The ETMS predictions can be improved by including in the calculation a factor for uncertainty. The new prediction model that was proposed and analyzed in this study took into account uncertainty in traffic demand predictions and showed improvements in both accuracy and stability of demand predictions compared to current ETMS.

The research was focused on analysis and characterization of errors in aggregate demand predictions inherent in ETMS and on improvements of ETMS predictions by using a new prediction model that includes, along with deterministic predictions for the 15-minute interval of interest, the predictions for two immediate adjacent 15-minute intervals (t-15) and (t+15). Including demand predictions for adjacent intervals would take into account possible random migration of some flights from one 15-minute interval to another during consecutive demand updates due to errors in predictions of flight arrival times. The new model was used for predicting demands at airports and sectors. The results of the study can be summarized as follows.

- Statistical analysis of ETMS historical data provided a characterization of the uncertainty in current ETMS aggregate demand predictions. Average errors and standard deviation of prediction errors were estimated at nine airports and thirteen en route sectors for various look-ahead times (LAT) ranging from 30 minutes to 6 hours.
- Linear regression was used to produce a new prediction model that improves accuracy of aggregate demand predictions.
- In the model calibration, parameters were estimated and analyzed. The analysis showed that relative allocation of regression coefficients was qualitatively similar in all cases considered. Namely, the demand prediction for a 15-minute interval of interest had the greatest coefficient, and the prediction at the immediate preceding 15-minute interval had a greater coefficient than the one at the immediate following 15-minute interval. The regression model reduced the standard deviation of demand prediction errors by 14 to 16 percent for airports and by 11 to 16 percent for sectors in comparison with the current ETMS predictions for all look ahead times.
- The new prediction model was tested on data not in the original calibration set for look ahead times ranging from 30 minutes to 2 hours. It showed an improvement in accuracy of demand prediction in comparison with the current ETMS predictions.
    - For airports, the reduction in standard deviation over the current ETMS predictions averaged 12 percent, and ranged between 2 and 20 percent, depending on the airport.
    - For en route sectors, the reduction in standard deviation over the current ETMS predictions averaged 12 percent, and ranged between 0 and 22 percent, depending on the sector.
- The new prediction model for airports also showed an improvement in stability of demand prediction in comparison with the current ETMS predictions.
    - When capacity was set equal to average demand, the number of changes in alert status decreased by 35 to 48%, depending on the airport.
    - Improvements in accuracy of demand predictions by the new regression model provide significant benefits for Monitor/Alert functions mainly in cases when predicted demand counts are in the vicinity of airport or sector capacity, when the instability and high fluctuations of successive demand predictions may cause significant instability and fluctuations (flickering) in detecting alert status.
- The study showed that the new demand prediction model reduced uncertainty in and improved the accuracy and stability of aggregate traffic demand predictions.

References

[1]Zobell, Stephen, Craig Wanke, and Lixia Song, "Probabilistic Airspace Congestion Management," Paper number 2005-7433, AIAA 5th Aviation, Technology, Integration, and Operations Conference (ATIO), Arlington, VA, 2005.

[2]Wanke, Craig, Lixia Song, Stephen Zobell, Daniel Greenbaum, and Sandeep Mulgund, "Probabilistic Congestion Management," 6th USA/Europe ATM R&D Seminar, Baltimore, MD, 2005.

[3]Meyn, Larry A., "Probabilistic Methods for Air Traffic Demand Forecasting," Paper number 2002-4276, AIAA Guidance, Navigation, and Control Conference and Exhibit, Monterey, CA, 2002.

[4]Smith, S. B., and Gilbo, E. P., "Analysis of Uncertainty in ETMS Aggregate Demand Predictions", Volpe National Transportation Systems Center, Report no. VNTSC-ATMS-05-05, November 2005.