Stochastic Airspace Demand for Strategic Traffic Flow Management

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Abstract— In this paper we consider the problem of predicting the demand for en route airspace sectors considering uncertain flight departure time and en route conditions. Flight, airport, and airline conditions that lead to greater variance in departure time prediction errors are examined and used to develop kernel-smoothed empirical probability density functions for flight departure time predictions. The structure of the departure time prediction errors is found to vary across the departing airport type. A similar analysis is performed for the en route airspace to characterize the random component of airspace sector traversal time. Variance of en route sector traversal times is found to increase for shorter duration planned sector traversal times. A method that combines these sources of uncertainty is presented and applied to two days of historical traffic conditions for east coast U.S. airspace sectors. Results of this analysis indicate that the mean absolute prediction error of the airspace demand can be reduced by 20% when using the probabilistic method as compared to a deterministic procedure. Similarly, standard deviation of the error in airspace demand is reduced by 23 to 25% also indicating a reduced spread in the demand estimation.

Keywords—en route; airspace; traffic flow management; demand; probabilistic

I. INTRODUCTION

In 2006 aircraft operating in the National Airspace System (NAS) experienced in excess of five hundred thousand aircraft hours of airborne delay [1]. The number and duration of delays are expected to worsen during a projected growth of 47.5 million to 67.7 million flights operating under instrument flight rules (IFR) from 2006 to 2017 respectively [2]. A combination of improved traffic flow management practices and an increase in airspace capacity would be required to mitigate these expected delays. The Next Generation Air Transportation System (NextGen) program is one such current initiative [3].

The focus of this work is to demonstrate how stochastic models can support en route traffic flow management decision-making under uncertainty. Current traffic flow management practice is based on the deterministic Enhanced Traffic Management System (ETMS) and the experience of air traffic controllers and managers [4]. ETMS provides forecasts of airport departures and arrivals, sector entry and exits, airway entry and exits, and waypoint crossings [5]. The drawback of these forecasts is the inability to consider a range of potential scenarios so that traffic flow managers must be more conservative in their decision-making. Conversely, the deterministic forecast may under-represent the congestion potential during volatile conditions, such as severe convective weather, leading to capacity overload.

There is a body of work in the recent literature focusing on quantifying and modeling stochastic elements of the NAS en route airspace. The estimated time of departure is the single largest source of uncertainty for flights that have not departed from the origin airport [6]. The work on pre-departure uncertainty has focused on quantifying variance and confidence bounds under various weather and flight-specific attributes at a range of look-ahead times [7-9].

The prediction of departure time is one component in the estimation of en route airspace sector demand. Meyn details a method to estimate sector and airport demand from arrival probability distributions and sector traversal time [10]. Only a single source of uncertainty is modeled at an unspecified look-ahead time. Mueller et al. note that departure time, wind forecasting errors, deviations from the flight plan, and aircraft performance and weight uncertainty can lead to errors in sector demand prediction [11]. The climb phase of flight, especially step climbs that are mandated by air traffic controllers in congested airspace, is identified as the source of the highest trajectory performance prediction errors with empirical results presented.

Flow models are another proposed approach to improve the estimation of sector demand by considering air traffic demand at a high level. Many of the current models are deterministic though well-suited to metering traffic flows to an arrival fix at a busy airport [12-15]. Probabilistic versions have also been developed but at the more macroscopic center level [16]. An attempt to establish a relationship between planned and observed sector counts is discussed in [17].

The following sections describe extensions to current stochastic airspace demand models to include pre-departure uncertainty, en route traversal uncertainty, and route uncertainty. A method to combine departure time uncertainty and en route traversal time uncertainty is presented and applied to one day of historical airspace conditions to quantify the benefit of a probabilistic approach.
II. DEPARTURE UNCERTAINTY

Previous work in the area of sector demand estimation has noted several factors that lead to errors in sector demand [6-8]. The work presented here will focus on pre-departure, sector traversal, and route uncertainty. Pre-departure uncertainty is the difference between the proposed wheels-off time at the origin airport and the measured departure time as recorded in ETMS. The ETMS system does not provide the most accurate historical prediction of wheels-off time, however errors of a few minutes are considered negligible in the context of this analysis.

The quantity of interest is the departure prediction error and not deviation from the schedule so the lateness of a flight is not what is being measured. The following is a partial list of factors that can result in poor estimations of departure time: aircraft arriving late from a previous leg, unavailable gates from the previous leg, crew arriving late, aircraft servicing, de-icing operations, runway direction reversals, taxiway availability, etc.

The procedure to calculate departure uncertainty begins by collecting all relevant messages from the ETMS historical data including the flight schedule (FS), flight plan (FZ), flight amendment (AF), control departure time (CTRL), and flight cancellation (RZ) messages. The analysis days for this study are shown in Table I from which 1,238,730 departure observations are extracted. Information from the previous day is also used to obtain full flight plan and schedule information. Gate push-back times are obtained from the FAA Airline Service Quality Performance (ASQP) database [18]. Definitions for departure time are shown in Table II.

Messages are then sorted by time of entry into the ETMS system. For each message a modeled departure time may be recorded at 0, 15, 30, 60, and 120 minute look-ahead times. A modeled departure time is not recorded if a more recent message is received prior to one of the look-ahead times.

<table>
<thead>
<tr>
<th>Day</th>
<th>Year(s)</th>
<th>Year(s)</th>
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<tbody>
<tr>
<td>February 19</td>
<td>2000-2005</td>
<td>September 26</td>
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<tr>
<td>May 10</td>
<td>2000-2005</td>
<td>October 23</td>
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<td>June 11</td>
<td>2004-2005</td>
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<td>2004</td>
<td>December 3</td>
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<tr>
<td>July 14</td>
<td>2005</td>
<td>November 28</td>
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</table>

TABLE II. DEPARTURE TIME DEFINITIONS.

- **NOTATION**: ETMS modeled departure time, ETMS modeled taxi time, Moving average of last five taxi times for that flight, Estimated runway-off time for flight from ETMS message, Wheels-off time – ETMS modeled departure time, ETMS modeled departure time – current time.
- **DEFINITION**: Gate push-back time + ETMS modeled taxi time, Moving average of last five taxi times for that flight, Estimated runway-off time for flight from ETMS message, Wheels-off time – ETMS modeled departure time, ETMS modeled departure time – current time.

For example if a flight plan message is received at 0200Z with a modeled departure time of 0330Z, then a subsequent flight amendment is received at 0250Z then only an error observation corresponding to a 60 minute look-ahead time is recorded for the 0200Z message.

The analysis proceeds by attempting to find structural variance in the prediction error data. Exploratory analysis strongly suggests the existence of non-constant variance across variables, otherwise known as heteroscedasticity. A modified least squares regression procedure is used since errors are non-normal and right-skewed even under a log transformation. Another method that accounts for non-constant variance is the class of generalized autoregressive conditional heteroscedasticity (GARCH) models most suitable to time series analysis but with limited applicability to this problem [19].

The modified regression procedure is as follows. The regression form of Error! Reference source not found. shows a response variable $Y$ to be a function of two independent random variables $X$ and $\epsilon$ and a coefficient matrix $\beta$.

$$Y = \beta X + \epsilon$$

If the variance is constant then $\epsilon \sim N(0, \sigma^2)$, and $X$ is independent of $X$. This model is extended by allowing the variance to be a function of $X$ as shown in and [20]. An exponential link function is used in this analysis but others may be substituted.

$$\epsilon \sim N(0, \sigma^2 \lambda(X))$$

$$\lambda(X) = \exp(\beta X)$$

This type of regression on the variance does not eliminate the non-normality problem but it does allow an investigation into the conditions that lead to larger variance. A total of 26 explanatory variables are considered representing flight, airline, airport, and weather conditions.

The model is calibrated using SAS [21] with coefficients for the 14 selected variables presented in Table III. The exponential of the coefficients is also shown since the coefficients must be transformed back and used as a multiplier effect. All variables are significant at the 5% level though the test for statistical significance is somewhat questionable in this case. A logarithmic transform of the error response at a 30 minute look-ahead time ($E_{LAT30}$) is used to better approximate normality.

$$Y = \log(E_{LAT30} + 60 \text{ minutes})$$

For the error could not be completely transformed to normality a categorical analysis of the distribution type of errors is considered based on the results of the regression analysis. The first of the groupings uses the departing airport type of the flight. A box-and-whisker diagram of the errors (Fig. 1) shows the 25th percentile, median, and 75th percentile of the errors as a box. The difference between the 75th percentile and the 25th percentile is known as the interquartile range.
considered valid if it is less than 1.5(IQR) from the box. Outliers are indicated by a “+”. The notable characteristics of the diagram are that the median is relatively constant between airport types, all the distributions are right-skewed (positively skewed), variance increases as airport size decreases, and there are numerous outliers for each distribution, which is the reason for the solid red line. Large variance for smaller airports may seem counter-intuitive but the type of airline operating at these airports has an impact.

A categorical grouping that includes factors in addition to departing airport size is shown in Fig. 2 with a corresponding box-and-whisker plot in Fig. 3. The clustering procedure covers all cases and the order is generally as follows: amendment, cancelled, forecasted convection, airport type, if the carrier is one of the top 25 carriers by operations, and arriving airport size. Clusters are ranked by mean error then by variance so that cluster 1 has the lowest mean and variance while cluster 10 has the highest mean and variance. The highest variance is for flights that have amendments or that have been cancelled and reactivated. By separating smaller carriers from larger carriers this analysis shows that larger carriers have lower variance than smaller carriers and smaller airports have lower variance than larger airports when corrected for carrier type. However, since smaller carriers dominate smaller airports we get the results shown in Fig. 1.

An attempt is made to generalize the errors to a probability distribution. However, since the error is right-skewed and peaked around 0 the standard distributions are poor approximations (Fig. 4). Histograms are constructed and compared to the lognormal for each of the two groupings considered here: airport type and clustered data. For each of these histograms the lognormal approximations are significantly different from the observed empirical distribution.

In kernel smoothing a probability mass, such as a normal or other symmetric density function, is placed at each data point. The equations to place the probability mass are straightforward. Begin by specifying a kernel that satisfies (5). In this case the standard normal distribution is chosen $K(x) \sim \mathcal{N}(0,1)$. The density at each value is estimated by summing all kernels as detailed in where $n$ is the number

![Figure 1. Box-and-whisker diagram for departure time prediction errors at 30 minute look-ahead times by departing airport type.](image-url)
The approach used compares the planned sector flight time to spend more or less time in the sector than planned. A pattern, or the clearance of a more direct route may cause the actions such as: speed changes, vectoring, issuing a holding demand is the traversal time through the sector. Controller route traffic control centers (ARTCCs): Chicago (ZAU), Indianapolis (ZID), Atlanta (ZTL), Jacksonville (ZJX), Miami (ZMA), Washington (ZDC), Cleveland (ZOB), New York (ZNY), and Boston (ZBW).

To obtain planned sector traversal times the most recent flight plan or amendment before the actual departure is extracted from ETMS data. The flight plan data is converted into a format suitable for the RAMS Plus airspace simulation software [22]. Other information including aircraft performance, airport locations, navigational aids (NAVAIDs), fixes, airways, standard terminal arrivals (STARs), and departure paths are also converted to the RAMS format. Aircraft performance uses EUROCONTROL’s Base of Aircraft DAta (BADA) [23] which is different from the ETMS system aircraft performance models [5]. The largest source of uncertainty in aircraft performance modeling is the prediction of aircraft weight. In this analysis we assume a nominal, or average, weight for each flight based on the three aircraft mass categories contained in BADA: low, nominal, and high. Each of the flight plans are then simulated to obtain the time of sector entry, time of sector exit, and sector traversal time. The air traffic controller functionality of RAMS is turned off so there is no conflict resolution for flights predicted to violate minimum separation standards.

The ratio of observed sector traversal time to planned sector traversal time, which is obtained from processing the RAMS output files, is examined for structure. A plot of the standard deviation of the ratio of observed to planned sector traversal times by planned sector traversal time and observed airspace density (Fig. 5) shows that the planned traversal time through the sector has a larger effect than the observed airspace density. This does not mean to suggest that airspace density has no effect since sectors with shorter traversal times are typically more congested than those with longer traversal times. The assertion here is that flown traversal time is mostly impacted by planned time for a flight to cross a sector.

Based on this observation a series of kernel-smoothed densities are developed for planned traversal times (t_p) as follows: \( t_p < 4 \text{ minutes} \), \( t_p \leq 8 \text{ minutes} \), \( t_p \leq 12 \text{ minutes} \), \( t_p \leq 16 \text{ minutes} \). A sample kernel-smoothed ratio for the 4 to 8 minute planned traversal time interval is shown in Fig. 6.

Alternatively, an error distribution that considers the relative difference between the observed and planned traversal times is also considered but not selected (i.e. error distribution = observed traversal time – planned traversal time). Due to the difference between the high and low range, e.g. 4 to 8 minutes in Fig. 6, a negative sector traversal time may be implied from the resulting error distribution. The ratio distribution is more appropriate in this case since traversal times are always positive and relative to the planned traversal time.

**III. SECTOR TRAVERSAL TIME VARIATION**

Another source of randomness in the estimation of sector demand is the traversal time through the sector. Controller actions such as: speed changes, vectoring, issuing a holding pattern, or the clearance of a more direct route may cause the flight to spend more or less time in the sector than planned. The approach used compares the planned sector flight time obtained through simulation to the observed sector traversal time from the processed ETMS radar track data (TZ). The scope of the analysis includes the following east coast air route traffic control centers (ARTCCs): Chicago (ZAU), Miami (ZMA), Washington (ZDC), Cleveland (ZOB), New York (ZNY), and Boston (ZBW).

To obtain planned sector traversal times the most recent flight plan or amendment before the actual departure is extracted from ETMS data. The flight plan data is converted into a format suitable for the RAMS Plus airspace simulation software [22]. Other information including aircraft performance, airport locations, navigational aids (NAVAIDs), fixes, airways, standard terminal arrivals (STARs), and departure paths are also converted to the RAMS format. Aircraft performance uses EUROCONTROL’s Base of Aircraft DAta (BADA) [23] which is different from the ETMS system aircraft performance models [5]. The largest source of uncertainty in aircraft performance modeling is the prediction of aircraft weight. In this analysis we assume a nominal, or average, weight for each flight based on the three aircraft mass categories contained in BADA: low, nominal, and high. Each of the flight plans are then simulated to obtain the time of sector entry, time of sector exit, and sector traversal time. The air traffic controller functionality of RAMS is turned off so there is no conflict resolution for flights predicted to violate minimum separation standards.

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**IV. SECTOR HIT RATE**

The last source of uncertainty considered in this analysis is the sector hit rate which is defined as the rate at which the planned sectors for a flight plan match the observed or flown...
sequence of sectors. It is a combined consideration of the route and altitude forecast accuracy. Consider ordered sets of planned sectors $P$ and flown sectors $F$. A hit is defined if the planned and flown sectors match and is then used to calculate the overall hit rate. Note that it is possible for a flight to enter the same sector more than once so by this definition the hit rate is restricted to be $\leq 1$.

$$\text{Hit Rate} = \frac{|P \cap F|}{|P|}$$

(7)

The simulation and playback results from the sector traversal analysis in RAMS are also used to calculate the hit rate. The results of the hit rate analysis show an overall average hit rate of 73%. Conditions that lead to re-routing such as severe weather and airspace congestion were not included here. Further work that could find a relationship to such as severe weather and airspace congestion were not included here. Further work that could find a relationship to predict sector hit rate probabilities under various conditions would be beneficial.

V. PROBABILISTIC SECTOR DEMAND

We now use the departure uncertainty and sector traversal variability models to develop sector demand at 10, 30, and 60 minute look-ahead times to sector entry. We are interested in the probability for a given flight to occupy a sector as a function of time (Fig. 7). The resulting distribution is not a probability density function since the area under the curve does not equal 1. This distribution would then be used in the calculation of sector demand by time period.

The equations in this section represent the application of standard statistical methods, such as the convolution theorem [24], and conventions used in calculations. The following nomenclature is used throughout this section:

- $\bar{d}_i(t)$ = Expected count, or demand, for sector $i$, during time period $t$
- $\rho_{\text{departure}}(r)$ = Distribution of errors in predicting a flights departure time as calculated in Section II for the flight traversing the sector at position $i$ under consideration
- $\rho_{\text{sector}}(r)$ = Distribution of flight traversal time through sector at position $i$ considering the stochastic en route component
- $\rho_{\text{random}}(r)$ = Probabilistic demand distribution for sector at position $i$ considering both departure and en route sources of randomness
- $\rho_{\text{ratio}}(r)$ = Distribution of ratio $r$ for sector $k$ as calculated in Section III
- $F = \{F_{\text{r1}}, \ldots, F_{\text{rm,n}}\}$ = Set of sectors traversed using the flight’s flown trajectory
- $i,j$ = Position indices where position $I$ is the first sector after the departing airport and positions $m,n$ are the last sector before the arrival airport
- $k$ = Sector index for ratio distribution $\rho_{\text{ratio}}(r)$
- $L_{\text{departure}}(\cdot)$ = Look-ahead time to departure (wheels-off)
- $L_{\text{sector}}(\cdot)$ = Look-ahead time to sector entry
- $m,n$ = Number of sectors that a flight crosses when following the flown $(m)$ or planned $(n)$ trajectory
- $P_{0}(F)$ = Probability that the flight under consideration arrives to a sector $i$ during time period $t$
- $P_{u}(F)$ = Probability that the flight under consideration does not arrive to a sector $i$ during time period $t$
Set \( P \) of sectors in the flight plan
\[
P = \left\{ \text{planned sector } \ldots \text{planned sector } \right\}
\]
Ratio of observed to planned traversal times
\[
r = \frac{S_{\text{traversal}}^\text{observed}}{S_{\text{traversal}}^\text{planned}}
\]
Sector in position \( i \) in the flight plan
\[
S^i_{\text{planned}} = \text{sector at position } i \text{ in the set of flown sectors } F
\]
Sector at position \( j \) in the set of flown sectors \( F \)
\[
S^j_{\text{flown}} = \text{sector at position } j \text{ in the set of flown sectors } F
\]
Planned time of entry into a sector at position \( i \)
\[
E^i_{\text{entry}} = \text{planned time of entry into a sector at position } i
\]
Planned traversal time through a sector at position \( i \)
\[
T^i_{\text{traversal}} = \text{planned traversal time through a sector at position } i
\]
Flown, or observed, time of entry into a sector at position \( j \)
\[
E^j_{\text{entry}} = \text{flown, or observed, time of entry into a sector at position } j
\]
Flown, or observed, traversal time through a sector at position \( j \)
\[
T^j_{\text{traversal}} = \text{flown, or observed, traversal time through a sector at position } j
\]
Variable used to convert from a ratio distribution to a relative error distribution
\[
r^\text{conv} = \text{variable used to convert from a ratio distribution to a relative error distribution}
\]

The analysis of historical ETMS data presented is sector based so to generate demand each sector in a flight plan is examined. To start we consider a single flight, its associated flight plan, and one of the sectors that the flight traverses when it follows its flight plan.

There are two cases to be considered for demand prediction for en route flights. There are additional considerations for flights that have not departed that are discussed later in this section. In the first case we find a flown sector that satisfies the conditions listed in (8-10). The first of these conditions is that the flown sector must also be included in the set of planned sectors. As shown in Section IV there are cases where the flown sector does not appear in the flight plan. The second condition ensures that the flown sector is at least the look-ahead time away from the planned sector. The third condition specifies that there is no closer flown sector.

So if a sector is found that satisfies the three conditions in (8-10) an improved estimate of the estimated sector entry time is calculated. Otherwise, for the second case where no sector is found that satisfies (8-10) the uncorrected planned time of entry into a sector is used which is the second condition in .

The next step is to determine the set of sectors for which traversal time ratio distributions will be considered and included in the analysis. If a flown sector is found that satisfies (8-10) then all sectors after and including the flown sector are included, otherwise all sectors are used to update the uncertainty distribution starting from the origin airport (12). Each of these sectors is matched with an appropriate ratio distribution that is described in Section III and categorized by the ratio of observed to planned sector traversal times (13). Since we are interested in the time relative to the corrected sector entry time calculated in we convert the basis of the distribution in . Planned traversal times are subtracted for all sectors excluding the planned sector under consideration so that all distributions are error distributions except the planned sector under consideration. For the planned sector under consideration the expected traversal time is included in the distribution to achieve a correct demand value.

\[
f = \begin{cases} 
  f_j, & \text{if } f_j \in P \\
  f_{\text{other}}, & \text{otherwise}
\end{cases}
\]

\[
f_{\text{ratio}}(r^j_{\text{traversal}}), \quad \forall k = j \ldots l
\]

\[
f_{\text{ratio}}(r^j_{\text{traversal}}), \quad \forall k = j \ldots l
\]

The distributions are summed by the standard convolution (i.e. the \(*\) operator) method of taking the
discrete Fast Fourier Transform $\mathcal{F}$ of each of the distributions, performing an element-by-element multiplication, then transforming back using the Inverse Fast Fourier Transform $\mathcal{F}^{-1}$ [24]. The general case is shown in for distributions $f(t)$ and $g(t)$ and in for the distributions considered here. If a sector is found satisfying (8-10) then the result of is the density function relative to the corrected sector entry time to be added to the sector demand. Otherwise the departure time prediction error is also considered.

If the departure time prediction error needs to be considered then the look-ahead time for the departure uncertainty is calculated using the look-ahead time to the sector, the planned entry time into the sector, and the planned flight departure. The departure look-ahead time is rounded up to one of the available departure look-ahead

$$f(t) * g(t) = \mathcal{F}^{-1}\{\mathcal{F}(f(t)) \cdot \mathcal{F}(g(t))\}$$

(15)

$$f_{\text{route}}(t) = \left[\left(f_{\text{route}}(t)\right) \cdots f_{\text{route}}(t)\right]$$

(16)
times of {0, 15, 30, 60, 120 minutes} and used to select a departure uncertainty distribution. The departure uncertainty distribution is combined with the en route uncertainty distribution to arrive at a total uncertainty distribution.

$$\text{LAT}_{\text{departure}} = \text{LAT}_{\text{sector}} - (f_{\text{departure}}(t) - f_{\text{route}}(t))$$

(17)

$$f_{\text{total}}(t) = f_{\text{departure}}(t) * f_{\text{route}}(t)$$

(18)

to estimate the demand for the planned sector under consideration during any time period a summation of the discrete total error distributions is performed. If a distribution of demand for a sector is required rather than just the expected count then a discrete probability density function is constructed for each flight consisting of the probability that the flight arrives during a time period $P_\alpha$ or does not arrive $P_0$. A series of convolution operators for each flight similar to that shown in may be used to derive a distribution of sector counts for the purpose of obtaining confidence bounds.

$$\hat{d}_i(t) = \sum_{\text{flight}} f_{\text{total}}(t)$$

(19)

$$p_i(t) = P(W = 1) = f_{\text{total}}(t)$$

(20)

$$p_0(t) = P(W = 0) = 1 - p_i$$

(21)

The method presented in this section implicitly assumes statistical independence for the departure and en route error distributions. Though this assertion is not strictly true it does allow for efficient demand uncertainty calculations. Methods that consider the covariance between the sector-based uncertainty distributions would also need to be computationally efficient to be useful for strategic traffic flow management.

VI. PERFORMANCE OF PROBABILISTIC SECTOR DEMAND MODEL

The historical traffic conditions on the date of August 29, 2005 is used to compare the performance of the probabilistic model for sector demand to a deterministic model at 10, 30, and 60 minute look-ahead times to sector entry in 1-minute intervals. Recall from the departure uncertainty section that two groupings are considered: one based on departing airport type and one based on a clustering that considers additional factors. Overall comparisons are made by considering the standard deviation of the demand prediction error and the mean absolute value of the prediction error (Table IV). The standard deviation of the error is reduced by 25% and the prediction error reduced by 20% when using the probabilistic methods as compared to the deterministic method. Results indicate that the cluster grouping method that considers additional factors offers little improvement on the method that only considers airport type in the departure uncertainty. Both methods also consider the en route random component as described in. A histogram detailing the distribution of the prediction error at a 30 minute look-ahead time to sector entry is shown in Fig. 8. This deterministic to probabilistic comparison is challenged by the fact that deterministic errors are discrete whereas the probabilistic errors may take on any real value.

Analysis of a second day of traffic data is performed for the date of July 27, 2005. The mean absolute prediction error for sector demand is reduced by 20% and the standard deviation by 23%, similar to the first day analysis results.

VII. CONCLUSIONS AND FUTURE WORK

In this paper departure time and en route sources of uncertainty are quantified. Airport size and sector traversal time are key indicators of the level of uncertainty expected for a flight. A probabilistic method is presented that combines airport and en route sources of uncertainty to produce improved estimates for sector demand. These more robust sector demand estimates have the potential to more efficiently use available airspace and identify volatile conditions that lead to higher controller workload. The probabilistic method is validated using historical traffic conditions for airspace sectors on the east coast of the U.S. for two days. Results indicate that the probabilistic method has the potential to reduce the standard deviation of the prediction error by 23 to 25% and the mean absolute prediction error by 20%. The sector hit rate, which is the rate that the planned sectors match the observed sectors, is a significant source of uncertainty for developing airspace sector demand estimates. Future work that can predict changes to the hit rate would be useful in improving sector demand estimates. Other future work could include identifying structure in the departure time and en route travel time error distributions.

VIII. ACKNOWLEDGEMENTS

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views of the authors and not those of the FAA or any other federal agency.

Figure 8. Histogram comparison of the distribution of sector count errors at a 30 minute look-ahead time on August 29, 2005 for deterministic and probabilistic (airport grouping) methods.

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<td>Sector Count Error (Observed - Predicted Count)</td>
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<tr>
<td>S.D.</td>
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<td>S.D.</td>
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<td>M.A.P.E.</td>
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<td>M.A.P.E.</td>
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<tr>
<td>M.A.P.E.</td>
</tr>
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- Standard deviation of the prediction error.
- Mean absolute value of the prediction error.
- Look-ahead time in minutes

REFERENCES