Modeling Air Traffic Demand for a Real-Time Queuing Network Model of the National Airspace System

Craig Wanke*, Christine Taylor†, and Tudor Masek‡
The MITRE Corporation, McLean, VA 22102

Sandip Roy§
Washington State University, Pullman, WA 99164

and

Yan Wan**
University of North Texas, Denton, TX 76203

Abstract

A predictive model for departure traffic demand and its route distribution at look-ahead times of 2-15 hours is proposed, for use in a queuing-network-based tool for strategic Traffic Flow Management (TFM). The proposed model uses a combination of operational data (filed flight plans, schedules), historical statistics of demand, and time-of-operation-specific factors to generate statistical predictions of traffic demand for particular routes between pairs of airports or airport clusters. Specifically, a two-stage predictor for demand is proposed. First, traffic demand for an origin-destination (O-D) pair is modeled as the summation of a known demand which captures filed and scheduled traffic, and an unknown demand which is modeled as non-homogeneous Poisson process. Second, the fraction of this O-D traffic demand on each route is modeled using a linear regression, with the historical route fractions, known (filed) route fractions, and wind-adjusted transit times for the routes serving as regressors. Historical data on demands and actual traffic volumes are used to evaluate aspects of the model, including the Poisson-process assumption and the regression model for route distributions.

I. Introduction

Strategic Traffic Flow Management (TFM) in the U.S. National Airspace System (NAS) is done today primarily by manual techniques, relying on human experience, intuition, and a variety of uncertain predictions of weather and traffic demand. In the Next Generation Air Transportation System, or “NextGen”, it is envisioned that automation will provide significant decision-making assistance for strategic TFM, in a process called Flow Contingency Management (FCM). Strategic TFM problems require predictions of weather and traffic flows from 2 to 15 hours in the future, and to be useful for decision-making, the ability to predict the consequences of proposed flow management actions is also needed.

A framework for an initial prototype of such a capability has been constructed. It employs a queuing network to represent traffic flows in the NAS, as due to the uncertainty of flight schedules many hours in advance, it is not appropriate or feasible to simulate individual flight trajectories. However, such models have traditionally been used for offline analyses, such as studies of NAS policy or structural changes, and so have used historical flight schedule information. To use such a model in predicting traffic behavior, a schedule of anticipated demand for the specific day of operation, conditioned on what is known at the time the prediction is made, is needed. This requires a blend of operational data (e.g., filed flight plans), historical demand statistics, and other factors that affect scheduling (e.g., wind predictions). Such a model is proposed here.

* Senior Principal Simulation and Modeling Engineer, Mail Stop N450, AIAA Senior Member.
† Lead Simulation and Modeling Engineer, Mail Stop N450, AIAA Member.
‡ Senior Operations Research Analyst, Mail Stop N450.
§ Associate Professor, School of Electrical Engineering and Computer Science, AIAA Member.
** Assistant Professor, Department of Electrical Engineering, AIAA Member.
II. Background

The queuing network structure is illustrated abstractly in Figure 1. Traffic enters the network at origin nodes (red-filled), which may represent one or a cluster of airports, and similarly leaves the network at destination nodes (green-filled). The full-resolution network is comprised of sub-networks for each origin-destination (O-D) pair. Nodes are also established at boundary crossing points (unfilled). Boundaries in this model can represent ATC sectors or en-route centers, depending on the level of detail needed.

The queuing model can be used to model flows and flow constraints in a flexible manner. Flow rates can be enforced at a boundary crossing, for example, to represent miles-in-trail (MIT) restrictions. Similarly, flow rates into a region can be modeled, and the effect distributed across the various O-D sub-networks, to represent an Airspace Flow Program (AFP). In this way, proposed traffic management actions can be modeled or designed. A complete description of the queuing model is provided in Reference 4. For the purposes of this work, it is sufficient to state that the model requires a stochastic description of air traffic demand for each O-D sub-network, further divided by the route of flight between origin and destination airports or clusters into origin-destination-route (O-D-R) subnetworks. Each route in the network connects the origin to the destination node and is defined by a series of sectors. These sector transits enable the O-D-R network to capture the aggregate propagation of flow across the NAS in a computationally-feasible manner. A detailed description of the O-D-R model can be found in Reference 5. The demand is modeled in aggregate terms, i.e. number of operations rather than individual flights. Note that most queuing network models are used for system analysis, rather than decision support, and thus can use historical traffic patterns for input. For real-time decision support, we need traffic demand that accurately reflects the current situation.

![Figure 1. Queuing network structure.](image)

Predicting demand volume given the route is a common need for TFM decision support tools, and it has been studied extensively in the context of tactical congestion management tools. Past work suggests that a reasonable model of aggregate demand for some NAS resources can be constructed for 15 minute prediction intervals by considering predicted filed and scheduled flights for the interval of interest, as well as those for the immediately preceding and subsequent intervals. This work was done for airport arrival and en route sector counts. In the context of sector counts, the previous method was extended to predict the statistical form and moments of demand distributions. The result was a 10-term linear model, in which predictions for filed, scheduled, and active (airborne) flights were considered in predicting the peak traffic count in a sector during a 15 minute interval. It included weights for these three predictions in the previous, targeted, and subsequent 15 minute intervals, and a constant factor to account for unknown traffic. Note that in Reference 9 it was shown that little or no value is gained by looking at intervals more temporally displaced than the adjacent ones. None of these studies specifically addressed estimation of departure demand at long look-ahead times (LATs).

At short prediction horizons (< 2 hours) it is safe to assume that most traffic of interest for a given resource is either airborne or has filed a flight plan, and thus making individual departure time and trajectory predictions for each flight is a good solution. At longer prediction horizons, many of the flights that will operate have not yet filed plans. Thus, much of the future departure demand is either made up of scheduled operations for which the route of flight is unknown, or of unscheduled traffic about which nothing is known. In today’s system, traffic managers rely on historical statistics to plan that far ahead. Thus, a hybrid model is needed which combines what is known about

American Institute of Aeronautics and Astronautics
operations on the current day with historical traffic patterns to provide useful traffic demand estimates in the strategic planning horizon.

For route-specific demand, there is little in the literature to work from. The current TFM automation system uses historically-flown route data to guess at the likely routes to be flown by scheduled flights that have not yet filed a flight plan, but this algorithm does not use wind or recently-filed flight plan information, and is not publically documented. For this application, we seek a general purpose algorithm that works on all projected demand (scheduled and unknown), conditioned on these factors as well as historical route usage.

III. Demand Model

A. Characterizing Demand

The demand modeling goal is to provide a stochastic, aggregate estimate of the number of operations as a function of prediction horizon, and the route distribution of that traffic, for each O-D pair of interest to the queuing network model. At a specific prediction time, the future demand can be split into three components:

1. Filed traffic: airborne IFR flights and pre-departure flights which have an active flight plan.
2. Scheduled traffic: flights which have a schedule entry for this day in the Official Airline Guide, or have had an ad-hoc schedule entry created by the airline on this day, but have not yet filed a flight plan.
3. Unknown, or “pop-up” traffic: flights that will depart during the planning period of interest, but about which there is no information available at the time of the prediction.

For filed traffic, both departure time and route information is available. For scheduled traffic, either no route information or an informed guess as produced by TFM automation is available. For unknown traffic, there is no information available. Thus, the missing information on the existence or routing of flights must be inferred from historical patterns, or other information available on the day of prediction, such as wind forecasts, or active traffic management actions that restrict or prescribe specific route usage.

In this context, demand must be strictly defined as the intent of aircraft operators to depart a flight at a given future time. If this occurs during a period of departure congestion, for example where the number of planned departures exceeds the available departure capacity, then the demand estimate should not change as a function of expected delays. Rather, it is expected that the queuing model (or whatever simulation model is using the demand estimates) should transform the excessive demand into delays if necessary. This complicates the use of measured operational data to estimate demand, as it is not always correct to use actual departure times to validate predicted demand; in some cases, filed information may also be adjusted to respond to either existing airport departure delay conditions or to delayed inbound flights to the origin airport of interest.

B. Goals

This model is intended to provide a 2-15†† hour forecast of O-D-specific aggregate traffic demand and O-D-R-specific route usage including uncertainty. Uncertainty will be provided both via statistical measures and via parameters for Monte Carlo simulation of a demand ensemble. The latter is more applicable to simulations in which flight counts must be expressed as integers for effective modeling (e.g., when simulating Ground Delay Programs).

The O-D realizations should support aggregation to provide input to higher-level NAS abstractions, such as when traffic flows are expressed as originating and/or departing from clusters of airports. Similarly, routing information should be expressed at a level which supports Air Traffic Control (ATC) sector-level airspace representation and higher abstractions of airspace (e.g., at an Air Route Traffic Control Center level).

C. Model Overview

We have chosen to model the number of operations on an O-D pair separately from modeling the route distribution, as these features should be largely independent. There are a variety of possible factors to consider, including but not limited to these:

1. Prediction horizon or “look ahead time” (LAT)
2. Predicted filed and scheduled departure counts (predicted demand)
3. Historical traffic levels, by time of day (TOD) and day of week (DOW)

†† Demand analysis examples in this paper are mostly focused on the 0-12 hour timeframe, but can easily be extended to 15 hours (or up to 24 hours) with additional data analysis.

American Institute of Aeronautics and Astronautics
4. Predicted demand in adjacent time intervals
5. Characteristics of origin and/or destination airport (satellite, hub, cargo, etc.)
6. Distance from origin to destination
7. Routes used earlier in this operational day
8. Winds aloft and winds aloft forecasts
9. Historical route usage
10. Active traffic management initiatives
11. Seasonal or longer scale variation in historical traffic levels and route usage

In this initial study, only the italicized factors were considered. The first three were studied in building the operations model, and factors 7-9 were considered in developing the route usage model. The other factors may affect either or both models, and will be considered in future work.

1. Operations Model

The number-of-operations forecast is comprised of two parts. The first is simply the known demand, as specified by filed and scheduled flight departure times over the next 12 hours. This is assumed to be deterministic, as it is an unambiguous and direct representation of what flight operators intend to do with those flights at this time. Note that there is uncertainty as to precisely when those flights will depart, but no quantifiable uncertainty about the intent of the operators to depart at the specified times.

The second part is the “unknown demand”, or unscheduled flights that plan to operate over the next 12 hours but for which we have no information. These may be ad-hoc airline flights, air taxi, cargo, or general aviation operations. Flight plans can be filed quite near the intended departure time, and are frequently filed less than an hour before departure. So for strategic traffic management purposes, we need to quantify the range of possible outcomes for these flights. The model proposed here assumes that the unknown traffic can be approximated by a non-homogeneous Poisson process (NHPP). The NHPP has been found to accurately represent many real-world counting processes in which disparate effects combine to produce a stochastic rate of events, including airport operations and en route traffic flows. Once parameterized, this model can be readily implemented in a Monte Carlo simulation procedure.

2. Route Usage Model

The route usage model is intended to estimate routes to be used by the portion of the demand that has not yet filed flight plans, comprised of the fraction of the known demand for which only schedule information is available and the unknown traffic as defined above. A regression model is proposed which uses quantitative metrics for factors 7-9 above to estimate the fractional usage of all O-D-R subnetworks which together make up a single O-D network. As with the operations model, this fractional usage can be directly implemented in a Monte Carlo simulation procedure.

IV. Developing the Operations Model

This section describes the modeling and analysis for the operations model. Specifically, the section describes the data collection, modeling techniques used and initial results obtained. As noted above, the demand model is needed for operations between individual airport pairs and between clusters of airports and therefore both types of flows were analyzed.

A. Parameterizing the Models from Operational Flight Data

The NAS-wide predicted and actual departure rates and routes used for June, July, August, and September of 2010 were collected from the Airline Situation Display to Industry (ASDI) data feed, and used for exploratory data analysis. In this context, the ASDI data provided scheduled flight entries (usually 24 hours prior to planned departure), filed flight plans, flight plan amendments, and departure reports. For rate analysis, each day was partitioned into 15 minute bins. For each combination of prediction time ($t_p$) and the future time for which the traffic would be forecasted ($t_f$), the actual and predicted departures were tabulated and classified by level of
knowledge {filed, scheduled, unknown}. The prediction “look-ahead time” (LAT) is given by the difference between these times.

The demand at \( t_f \) is defined as the sum of “known” and “unknown” demand components. The “known” demand component includes those flights which have filed flight plans or schedule entries at time \( t_p \) indicating that they will depart during the 15-minute bin starting at \( t_f \). The “unknown” demand component includes those flights that actually depart during the 15-minute bin starting at \( t_f \), but do not have a flight plan or schedule entry for any departure time at \( t_p \), and were hence unknown to any observer or automation system at that time.

This initial study was focused on determining the relative importance of the possible factors listed above, and to develop a preliminary version of the model for verification and validation activities. The results of this analysis are described below.

B. Traffic Counts

Flights between individual airport pairs are relatively few in a given day; one of the busier O-D pairs, Newark Liberty International Airport (EWR) to Miami International Airport (MIA), averaged just over 8 flights per day\(^{14}\) during the summer of 2010. Many pairs will have only one or two flights per day. Hence some of the statistical analysis is based on the cluster data, and the findings extrapolated to individual airport pairs. The cluster statistics will also provide a way to check the O-D pair demand models contained within them.

\[\text{Figure 2. Departure counts for the EWR cluster to MIA cluster flow.}\]

Actual traffic from the EWR cluster\(^{1**}\) to the MIA cluster\(^{1***}\) in June, July, and August of 2010 is summarized in Figure 2 as a function of TOD and DOW (expressed in Universal Coordinated Time, UTC). Traffic is very low over

---

\(^{14}\) Because this is based on the ASDI data, it may fail to include a small number of flights which are excluded from that data feed. Also, Visual Flight Rules (VFR) operations are not included.

\(^{1**}\) The EWR cluster contains EWR, John F. Kennedy International (JFK), LaGuardia (LGA), Teterboro (TEB) and 16 smaller airports: HPN, ISP, MMU, FRG, SWF, BDR, HTO, FOK, HVN, OXC, CDW, DXR, POU, MGJ, LDJ, MSV

\(^{1***}\) The MIA cluster contains MIA, Fort Lauderdale (FLL), West Palm Beach (PBI) and 37 smaller airports: RSW, FXE, EYW, SRQ, OPF, MLB, TMB, FPR, VRB, APF, ISM, BCT, FMY, SUA, LAL, MTH, LNA, TIX, HWO, VNC, SPG, PGD, BOW, COL, OBE, PHK, SEF, GIF, ASD, HST, NQX, IMM, MCF, AVO, TNT, COF, AGR
the night hours, and relatively steady throughout the day, peaking at around 10 departures in any single hour. There is some visible variation with respect to DOW, so a comparison of the overall daily mean departures was done. Figure 3 shows the data distribution across days of the week at left. The green “means diamonds” in the figure are used for statistical significance comparison; the horizontal lines indicate the mean and 95% confidence bounds, and individual means are different by an 0.05 significance criterion if the diamonds do not overlap.

The results of a Tukey-Kramer Honest Significant Difference (HSD) test are shown at right, both via “means circles” and a table of numerical results. Circles for means that are significantly different either do not intersect, or intersect slightly. In the table, means with the same capital letter (level) are not significantly different from each other, but do differ from means with different letters. This result suggests a slight but statistically-significant difference in the means across DOW, most importantly that Sundays have significantly less traffic than the rest of the week (i.e. one could group this flow into Sunday and every-other-day at the 5% significance level).

![Figure 3: Daily variations in departure count, EWR cluster to MIA cluster.](image)

Figures 4 and 5 repeat this analysis for the flows specifically from EWR airport to MIA airport. The traffic levels are obviously much lower, rarely having more than two departures in any given hour, but similar patterns as before are observed. In this case, the means comparison shows that the total number of flights in a day could be placed in three groups, again with Sunday on its own. Note that for the purposes of demand modeling, DOW effects must be captured in the context of specific predictions at different times of day; the purpose of looking at the daily mean departure counts is simply to explore the magnitude of the effect of DOW on overall traffic levels. Similar behavior is observable in other O-D flows, and is omitted here for brevity.
Figure 4. Departure counts for the EWR-MIA flow.

Figure 5: Daily variations in departure count, EWR-MIA flow.
Given these general traffic characteristics, what specifically is known about future departures, and when? Figure 6 illustrates several days of samples taken at 1500z prediction time for the EWR cluster to MIA cluster flow. The upper chart shows how many filed or scheduled flights intend to take off (in 15-minute bins) for the next 12 hours (720 minutes) with each of the sample days shown on a separate horizontal line. The lower chart shows the flights that departed in each of those bins about which nothing was known at the prediction time. As expected, the known demand is fairly consistent day-to-day, but the unknown demand exhibits considerable variation. It is also apparent that the unknown demand is a significant contributor to the overall volume of traffic.

Figure 6. Known and unknown demand events for 7 days of the EWR-cluster to MIA-cluster flow.
Similar plots for 12 days of 1500z predictions from EWR airport to MIA airport are given in Figure 7. The normal daily traffic is evident in the upper plot, consistent from day to day, with what may be a slight schedule change seen for the later flight, and perhaps some day-to-day variation is what is known at 1500z. The highest number of known flights is 5, as seen on days 20, 22, 23, 25, and 27. No unknown flights show up for these predictions. When some expected known flights don’t show up, they frequently appear in the unknown demand, presumably changing over to “known” as flight plans are filed later in the day (see days 19, 21, 24). Sometimes the flights operate later than they usually do, indicating that there may be disruptive events occurring (see day 28). Schedule variation may also be visible; note that on Sundays (days 19, 26) the flight that usually operates at around 600 minute LAT does not exist in either event chart.

Figure 7. Known and unknown demand events for 12 days of the EWR to MIA flow.
This example suggests that most flights from EWR to MIA are regularly scheduled operations. As a comparison, Figure 8 describes 10 days of 1500z predictions for flights from Teterboro Airport (TEB) to Westchester County Airport (HPN), as an instance of a non-trivial flow without major airline service. In this case, very little is known about future demand at 1500z – only three known flights show up across all 10 days – but the unknown demand traces show between 1 and 5 departures over the next 12 hours, with no recognizable patterns.

Figure 8. Known and unknown demand events for 10 days of the TEB to HPN flow.

C. Characterizing Uncertainty

The above results suggest that we need to consider DOW and the known demand in order to predict the unknown component of the demand. Though not directly shown, TOD is also a strong factor, due to flight scheduling and the propensity of even unscheduled flights to follow patterns (e.g., cargo flights tend to occur in the late evening and early morning). The effect of known demand is harder to model, since in some cases it is strongly related to unknown demand (Figure 7) and seemingly unrelated in others (Figure 8). Arguably the EWR-MIA flow could be purely modeled by a historical schedule, only adjusting departure times when new information is obtained. Clearly, TEB-HPN cannot be modeled this way, and other O-D pairs (especially clusters) exhibit a mix of these characteristics. We choose here to continue with statistical modeling, informed by historical counts, to try to capture both characteristics simultaneously.

Figure 9 presents the mean and variance of the unknown demand components for the EWR cluster-to-MIA cluster flow, over all predictions made at 1500 UTC, and broken down by the number of flights in the known demand. Flight values for both known and unknown demand are in reference to the 15 minute data collection periods (i.e. “mean flights per 15 minute period”). For this analysis, the DOW effect is ignored, though it can be readily captured through grouping of similar days as described previously. The data is further classified by LAT in 12 one-hour bins. Our hypothesis is that the stochastic unknown demand count \( N \) occurring in an LAT period of length \( \tau \) and known demand value can be adequately represented by a Poisson random variable:

\[
\Pr[N = k] = \frac{(\lambda \tau)^k e^{-\lambda \tau}}{k!}, \quad k = 0, 1, 2, \ldots
\] (1)

Where the parameter \( \lambda \) represents the (constant) expected number of arrivals per unit time, and for the data collected here, \( \tau = 15 \) minutes. Also, we hypothesize that \( \lambda \) is primarily a function of LAT and known demand. Note that a fundamental property of Poisson distributions is that the mean and variance are equal, specifically:
At first glance, this appears to be true for most of the data points in Figure 9. To further test the hypothesis that the Poisson distribution is appropriate, Pearson’s Chi-squared goodness-of-fit tests were run for all bins where the number of samples (N) is at least 30, and the normalized Chi-square value is shown as green points. Values near 1 indicate a good fit with the Poisson distribution, and values less than a designated significance level (a value of 0.05 was chosen here) can be interpreted to reject the hypothesis that the data arises from a Poisson distribution. By this criterion, the Poisson distribution hypothesis was rejected for only two of the 36 distributions, both in the 0-1 hour LAT bin. These cases also show significant difference between the measured mean and variance. There are a few other cases where the Chi-square statistic is well under 0.5, indicating a poor fit. In several of these cases, it is also apparent that there is a noticeable difference between the mean and variance of the measured distribution. But overall, these results are promising.

Note that there are two other conditions that must be satisfied for this to truly be a Poisson process. First, we would need to demonstrate that the interarrival times are Poisson-distributed, not only (as we have done) that the resulting counts are Poisson-distributed. This requires a different kind of data collection in which we capture the precise departure times for each unknown flight, rather than only which 15-minute bin they depart in. Second, we would need to demonstrate that counts in adjacent LAT intervals are uncorrelated, or at least sufficiently uncorrelated that the Poisson process hypothesis is sufficiently accurate. This will be explored in future work.

\[ E(N) = \sigma^2(N) = \lambda \tau \]  

Figure 9. Normalized mean and variance of unknown demand as a function of normalized known demand and one-hour LAT bin, for the EWR cluster-to-MIA cluster flow, across all predictions made at 1500 UTC, with Poisson distribution fit metrics.
Figure 10. Mean and variance of unknown demand as a function of known demand and two-hour LAT bin \((N \geq 30)\), for the EWR cluster-to-MIA cluster flow, across all predictions made at 1500 UTC, with Poisson distribution fit probabilities.

For comparison, Figure 10 shows a similar analysis where the data is classified by two-hour LAT bins. While it is desirable to increase bin size to reduce the number of parameters, the goodness-of-fit tends to suffer as well. The results here are not conclusive, but at least one additional case where the Poisson fit hypothesis is rejected is shown for half as many total distributions.

An alternate method was tried by grouping the known and unknown traffic together across each bin (1 hour, 2 hour) interval, and testing if the result was well-modeled by a Poisson distribution. It did not, though in many cases it was well modeled by a Gamma-Poisson distribution which is indicative of a process composed of the sum of multiple Poisson sub-processes with different values of \(\lambda\). This confirms that it is necessary to allow each 15 minute LAT interval to have a different value of \(\lambda\), even if the selection of \(\lambda\) is done using coarser LAT bins or groupings of known demand and/or DOW.

**D. Proposed Model Form**

After further exploration of cases like that depicted in Figure 9 with varying bin sizes and data sets, it was decided to assume the following:

- It is reasonable to represent the unknown demand distribution for each 15-minute LAT period as a homogeneous Poisson process.\(^{†††}\)
- LAT bins of one hour are appropriate for classifying the distribution. While more accuracy could be gained with smaller bins, much more data would need to be collected to get valid statistics, and the time span over which the data would need to be collected would become so long that other factors may become significant (e.g., seasonal variation in schedule).
- The rate in a bin is a function of at least O-D pair, TOD and known demand, and it may be necessary to include DOW groups as well.

\(^{†††}\) Setting a constant bin size carries the the risk of missing important features of the process being modeled. An alternate non-parametric method was developed by Leemis\(^{18}\) assuming a piecewise-linear form of \(\lambda(t)\) which naturally arises from the event times in the data samples. Our data collection was not precise enough for this type of model – we only record in which 15 minute bin an event occurred - but it is a possible avenue for further work.
This suggests a specific form of non-homogeneous (time-varying) Poisson process model where the rate parameter $\lambda(t)$ is piecewise-constant, the values for which can be estimated simply by taking the sample mean of each bin defined by \{O-D pair, TOD, known demand, DOW\}. Thus, each 15-minute LAT period $i$ has a corresponding value $\lambda_i$. The cumulative intensity function for an NHPP provides the expected number of events that occur by a time $t$, and is defined in the general form as:

$$\Lambda(t) = \int_0^t \lambda(\tau)d\tau$$  \hspace{1cm} (3)

Which for the piecewise-constant $\lambda(t)$ implies that the expected number of unknown flights $U$ by the end of the $k^{th}$ period is given by:

$$U = \sum_{i=1}^{k} \lambda_i \Delta$$  \hspace{1cm} (4)

where $\Delta = 15$ minutes, and $\lambda_i \Delta$ is the sample mean for the conditions that exist in LAT bin $i$, for example those plotted in Figure 9. Values are being tabulated for several prediction conditions in order to determine how well the real statistics are matched by this model, but results are not available at this writing.

**E. Monte Carlo Implementation**

The piecewise-constant NHPP was implemented for Monte Carlo simulation using the “thinning method.” Figure 11 shows three sample Monte Carlo variates for the $5^{th}$ prediction day shown in Figure 6. Qualitatively, the event sequence is similar. As noted above, more analysis is required to determine how well we are reflecting the real-world statistics of this process.

![Figure 11. Sample sequences of Monte Carlo-generated events for Day 5 of the EWR cluster-MIA cluster flow prediction described earlier in Figure 6.](image)

**F. Issues and Further Work**

The MATLAB simulation implemented in this work can build 1000 outcomes in a few seconds, which would likely be speeded up with implementation in a high performance computing language. The method is also easily parallelized across O-D pairs. However, considerable work remains to be done to build a general purpose demand generator.

The largest task is to construct and periodically update the table of Poisson parameters for all O-D airport and cluster pairs in the NAS (or for whatever domain is of interest). Aside from the large number of O-D pairs – even the fully-clustered model contains 52 airport clusters, for which each pairwise flow needs to be parameterized across all independent variables – the NAS is a non-stationary system, with continually-changing flight schedules. So a robust updating procedure is also needed.

Also, though a Monte Carlo simulation of a single O-D pair is not time-consuming, simulating all pairs for a usefully-sized problem may pose a challenge. Parallel computing can help, but further study is needed to determine both how many Monte Carlo replications are needed for specific applications, and to develop efficient computational techniques.

Finally, model validation is needed. Any stochastic traffic model requires considerable data analysis to establish statistical validity of means and variances, at a minimum.
V. Developing the Route Usage Model

This section describes the separate analysis conducted for the route utilization prediction component of demand modeling. Within this section we describe the factors considered for route utilization, the prediction model developed and provide an analysis of the initial results generated.

A. Factors influencing route utilization

Nominally, historic utilization of routes is a major factor influencing the prediction of route utilization. Given a sufficiently long time period for historic collection, these previously used routes and associated usage fractions define (for each O-D pair) the preferred route utilization as well as desired alternates. However, on a given day, the actual distribution may be skewed given weather or other operational concerns. We propose that these day-of factors can be classified as planned or reactive factors. Planned factors refer to a change in the route utilization fractions resulting from day-of positive attributes associated with a given route, such as location of the route relative to the jet stream. Reactive factors characterize route selections defined by airspace users to offset predicted or impending constraints in the NAS, such as convective weather blocking desired routes or high congestion. For our initial model, we aim to capture the planned factors and evaluate their performance for predicting planned route utilization.

Capturing user intent is a serious challenge due to the proprietary nature of the user goals; however we believe that we can derive the impact of preferences from available data. It is important to note that although different users may have different goal functions, as FCM is a flow model, which does not differentiate between aircraft, we are instead seeking an aggregate response to conditions. Specifically, we will assume that the following factors signal a desire of users to utilize specific routes.

1. Historic utilization provides an aggregate picture of the general desirability of routes. Although some plans may have been created in response to reactionary factors, over a sufficiently long period, general trends will emerge
2. Wind-adjusted route transit times provide an estimate of the average transit time associated with a given route. As shorter route transit times utilize less fuel and are of potentially lower cost to the airlines, we propose that using wind-adjusted transit times will capture the desirability of using a specific route.
3. Previously filed routes can be utilized to capture the number of other planned factors that might influence a given route’s desirability. As such, we will capture the filed routes over a short period prior to the analysis time, in order to capture day-of preferences not captured within the other factors.

B. Route Utilization Prediction Model

We seek to define a formula that weights the above components to determine the fraction of utilization for each route, where the weightings are assumed to be specific for each O-D pair. Our initial model assumes a linear relationship of the factors. Specifically, for each O-D pair, we seek the fraction of demand travelling on route and denote this as . Equation 5 defines the relationship of the planned factors for predicting the demand on route for each O-D pair.

\[
r_j = \alpha_h h_j + \alpha_w w_j + \alpha_f f_j
\]

In Equation 5, represents the historic fraction of traffic traveling route , represents the relative wind-adjusted transit time value of route , and represents the fraction of filed traffic travelling on route . The coefficients , , and represent the weighting factors that determine the impact of each of these factors on the overall routing.

An additional constraint that must be considered when developing these relationships is that for each O-D pair, the sum of all route fractions must equal one, as defined in Equation 6.

\[
\sum r_j = 1
\]

---

The transit time associated with a given route is the average transit time of all flights travelling the route in the historic collection period. As such, these times represent the average over all aircraft equipment profiles. However, given that the purpose of computing the wind-adjusted transit time is to define the relative desirability of the route on a given day, using an average transit time as a baseline is reasonable.
To accommodate this constraint easily, we propose to scale each factor to represent a fraction whose sum across all routes is one. This modeling choice also implies that the weighting coefficients also sum to one, as shown in Equation 7.

$$\alpha_h + \alpha_w + \alpha_f = 1$$  \hspace{1cm} (7)

Furthermore, for consistency, we define each factor such that the larger the fraction, the more desirable the route. The remainder of this section will detail the definition of each factor and the coefficients.

### 3. Definition of Factors

#### a. Historic utilization factor

Historic utilization of a route is computed from the first filed flight plans collected over the period of historic data collection. Routes derived from filed flights are used, as opposed to the routes actually flown, to mitigate the influence of reactive factors or tactical maneuvers on the flight plan. Similarily, first filed plans are used, as opposed to last pre-departure flight plans, to estimate initial operator intent, free of influence from other factors such as delay and/or congestion that may necessitate subsequent flight plan updates. By aggregating utilization data from a sufficiently long historic horizon, we collect multiple options and determine the average likely utilization. The historic utilization of each route can be calculated as shown in Equation 8:

$$h_j = \frac{h_{uj}}{\sum_i h_{uj_i}}$$  \hspace{1cm} (8)

where $h_{uj}$ is the historic utilization of route $j$. We note that the historic utilization of a given route is defined for each OD pair independently. The above definition of $h_j$ will be a fraction between 0 and 1, where larger values indicate higher preference for utilization and the sum over all routes for the OD pair will equal one.

#### b. Wind-adjusted transit time factor

The wind-adjusted transit time of each route are computed using the average true air speed associated with each route as well as the latest Rapid-Update Cycle **** (RUC) model forecast to estimate wind speed. The RUC wind forecast is produced each hour and includes the now-cast as well as hourly predictions out 18 hours. However, as wind forecasts are generally stable, and forecasts at shorter LATs are more accurate, we use the latest now-cast of winds to perform the prediction.

Using the latest now-cast, the wind adjusted transit times are computed for each route and each O-D pair. The wind-adjusted transit time factor is then computed as shown in Equation 9:

$$w_j = \frac{1 - t_j}{N - 1}$$  \hspace{1cm} (9)

where the wind-adjusted transit time for the given route is defined as $t_j$, and $N$ is the number of routes for the O-D pair. This definition of the wind-adjusted transit time factor ensures that the fraction increases with decreasing transit time and that the sum over all routes for an O-D pair equals one.

#### c. Filed route factor

The filed route factor is an estimate of the flow fraction on each route based on day-of filed flight plans. Specifically, we collect the first filed flight plan for each flight and determine the filed frequency, or utilization, of each route for each O-D pair. Thus for a given day, the filed route factor is defined as shown in Equation 10:

$$f_j = \frac{u_j}{\sum_i u_j}$$  \hspace{1cm} (10)

where $u_j$ is the utilization of the given route in the filed flight plans on the previous day. This definition ensures that the fraction increases in value as a given route is filed more frequently and sums to one across all routes in the O-D pair. As the number of filed flight plans can be small for a given O-D pair, we will utilize the previous 24 hours of filed flight plans.

4. Regression Model for Coefficients

Using the above defined factors, we propose a regression model to determine the coefficients in Equation 5. As such, we modify Equation 5 to represent the definition of the regression model for each day of data, defined as data set $k$, as shown in Equation 11. We also assume that this regression is performed for each O-D pair separately.

\[
\bar{r}_j^k = a_h h_j + a_w w_j^k + a_f f_j^k
\]

(11)

Here, $\bar{r}_j^k$ is the calculated route utilization fraction, derived from the coefficients and the calculated factors using data set $k$. We first discuss how each factor is defined and then present the regression model that will determine the coefficient values.

The historic route utilization factor is a constant for all data points as it is defined by the utilization over the entire data collection period. The wind-adjusted transit times for each route are defined using the first now-cast from the RUC forecast at the beginning of each day $k$. The filed route factor uses the previous day’s filed routes to define the utilization fraction for this factor. Initially, we assume that the previous day’s plans are utilized, which corresponds to defining the analysis at the beginning of the day. However, future research may explore how moving this horizon to later in the day, thereby capturing day-of plans, might improve the estimate.

To define the regression, we simply minimize the absolute difference between the computed route utilization value, $\bar{r}_j^k$, and the actual route utilization value, $r_j^k$, as shown in Equation 12:

\[
\min \sum_i \sum_j |\bar{r}_j^k - r_j^k| \tag{12}
\]

where the actual route utilization is computed using the first filed flight plans on the $k^{th}$ day. In addition, to ensure that the sum of the utilization fractions for each day is 1, we add the following constraint:

\[
a_h + a_w + a_f = 1 \tag{13}
\]

C. Initial Data Collection and Analysis

To develop and analyze the above defined model, we collected filed flight plan data for the period between July 30, 2010 and September 30, 2010. Furthermore, we assumed a baseline sectorization for consistency in route definition. The regression and prediction analysis was performed for a small set of O-D pairs, namely pairs consisting of Hartsfield-Jackson Atlanta International Airport (ATL), Charlotte Douglass International Airport (CLT), Denver International Airport (DEN), Dallas Fort Worth International Airport (DFW), Los Angeles International Airport (LAX), John F. Kennedy International Airport (JFK) and O’Hare International Airport (ORD).

The O-D-R network that defines the available routes for the selected O-D pairs spans this entire time horizon of data collection, and the historic utilization fraction is readily computed from the usage statistics provided in the network. In addition, true air speed is computed for each route segment, using interpolation of air speed estimates from the trajectory modeler that defines the network sector transits associated with each filed flight plan. The daily wind-adjusted transit time was calculated for each route using the average true air speed estimates for each route and the 0Z RUC wind forecast for each day.

To determine both the filed fractions as well as the actual fractions, we utilize the daily records provided by the same trajectory modeler for each day in the time horizon under consideration. The actual fractions are computed from the utilization of routes over a 24 hour period, while the filed fractions are computed from the utilization of routes over the previous 24 hours. Thus the 63 days collected provide 62 data points, as the first day collected can only provide the filed flight plans for analysis of the second day.

Finally, to perform and test the model proposed, the data is divided roughly in half, where the period of July 30, 2010 to August 28, 2010 is utilized to define the regression parameters, and the remaining dates are utilized to test the error associated with the predictive model.

5. Analysis of the regression and prediction results

Using the above defined model, we generated coefficients for each of the factors and computed the average error and variance associated with the regression for the sample data considered. Table 1 displays the results. Examining Table 1, we see that all O-D pairs have a coefficient value of 0 for the wind adjusted transit time factor, which implies that this factor has no impact. At first, this result was surprising; however differences between route transit time factors were very small, even when an exponent was applied to the transit time ratio to magnify differences. Examining the transit time factor over a small sample of the days showed little correlative evidence could be
gleaned from the factor on a single day, and therefore, the factor was not useful when evaluating a number of days within the regression.

Focusing on the remaining two factors, another interesting trend can be seen. Specifically, for 17 of the 42 to O-D pairs evaluated, the filed flow fraction coefficient is one and the historic flow fraction is zero. This implies that for 40% of the O-D pairs considered, historic route utilization is not a useful predictor of day-of routing. For the remaining O-D pairs that utilize both historic and filed flight plans to predict day-of routing, only 10 city-pairs weight the historic flow fraction greater than 25% and only one (JFK to ATL) has more than half of the day-of prediction determined by the historic fraction. However, it is important to note that the average regression error is slightly higher for O-D pairs where only the filed flow fraction coefficient has a non-zero weighting.

Using these coefficients, we predict the flow fraction for each route of the O-D pairs using the historic and filed fractions, and compare this to the actual filed flight plans on those days. The average error and variance associated with the predictions for each O-D pair are displayed in Figure 12.

<table>
<thead>
<tr>
<th>Origin</th>
<th>Destination</th>
<th>$\alpha_h$</th>
<th>$\alpha_w$</th>
<th>$\alpha_f$</th>
<th>Average Error</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALT</td>
<td>CLT</td>
<td>0.362</td>
<td>0</td>
<td>0.638</td>
<td>0.025</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.012</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0.204</td>
<td>0</td>
<td>0.796</td>
<td>0.031</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0.466</td>
<td>0</td>
<td>0.534</td>
<td>0.038</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.014</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.226</td>
<td>0</td>
<td>0.774</td>
<td>0.014</td>
<td>0.001</td>
</tr>
<tr>
<td>CLT</td>
<td>ATL</td>
<td>0.081</td>
<td>0</td>
<td>0.919</td>
<td>0.028</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.019</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.020</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.028</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.035</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.172</td>
<td>0</td>
<td>0.828</td>
<td>0.016</td>
<td>0.002</td>
</tr>
<tr>
<td>DEN</td>
<td>ATL</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.014</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>CLT</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.041</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0.411</td>
<td>0</td>
<td>0.589</td>
<td>0.015</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.037</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0.288</td>
<td>0</td>
<td>0.712</td>
<td>0.013</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.219</td>
<td>0</td>
<td>0.781</td>
<td>0.013</td>
<td>0.001</td>
</tr>
<tr>
<td>DFW</td>
<td>ATL</td>
<td>0.330</td>
<td>0</td>
<td>0.670</td>
<td>0.021</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>CLT</td>
<td>0.164</td>
<td>0</td>
<td>0.836</td>
<td>0.028</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0.132</td>
<td>0</td>
<td>0.668</td>
<td>0.014</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.034</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0.061</td>
<td>0</td>
<td>0.939</td>
<td>0.025</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.068</td>
<td>0</td>
<td>0.932</td>
<td>0.015</td>
<td>0.003</td>
</tr>
<tr>
<td>JFK</td>
<td>ATL</td>
<td>0.656</td>
<td>0</td>
<td>0.344</td>
<td>0.025</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>CLT</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.026</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.027</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.030</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.095</td>
<td>0</td>
<td>0.905</td>
<td>0.018</td>
<td>0.003</td>
</tr>
<tr>
<td>LAX</td>
<td>ATL</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.015</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>CLT</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.042</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0.153</td>
<td>0</td>
<td>0.847</td>
<td>0.018</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.015</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0.129</td>
<td>0</td>
<td>0.802</td>
<td>0.008</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>ORD</td>
<td>0.381</td>
<td>0</td>
<td>0.619</td>
<td>0.009</td>
<td>0.001</td>
</tr>
<tr>
<td>ORD</td>
<td>ATL</td>
<td>0.314</td>
<td>0</td>
<td>0.686</td>
<td>0.016</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>CLT</td>
<td>0.223</td>
<td>0</td>
<td>0.777</td>
<td>0.023</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>DEN</td>
<td>0.252</td>
<td>0</td>
<td>0.788</td>
<td>0.012</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>DFW</td>
<td>0.196</td>
<td>0</td>
<td>0.804</td>
<td>0.012</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>JFK</td>
<td>0.373</td>
<td>0</td>
<td>0.627</td>
<td>0.019</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>LAX</td>
<td>0.202</td>
<td>0</td>
<td>0.798</td>
<td>0.007</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Examining Figure 12, we see that the prediction error varies greatly by O-D pair, with some O-D pairs showing small errors and low variances for the predictions over the data set while others display poor prediction quality. Although no strict correlation of prediction quality is discernible from Figure 12, we do see some qualitative trends emerge. The average error and variance across all O-D pairs is 1.82% and 0.5%, respectively. However, the predictions for flows to and from LAX and ORD yield smaller errors and variances. Specifically, the route utilization predictions for flows originating at LAX have an average error and variance of 1.00% and 0.21%, respectively. Routing predictions for flows terminating at LAX have an average error and variance of 1.25% and 0.24%, respectively. The routing predictions for flows originating at ORD have an average error and variance of 1.31% and 0.17%, respectively, and flows terminating at ORD have an average error and variance of 1.12% and 0.15%, respectively. Thus, the proposed model predicts the routing fractions for these O-D pairs reasonably well.

In contrast, the utilization prediction for flows originating at DFW has an average error and variance of 2.35% and 0.80%, respectively, and the utilization prediction for flows terminating at JFK has an average error and variance of 3.51% and 1.36%, respectively. Interestingly, the lowest average error between two O-D pairs is 0.03% for flows originating at LAX and terminating at JFK while the highest average error between two O-D pairs is 6.49% for flows originating at DFW and terminating at JFK.

2. Analysis of DFW to ATL for congestion prediction

In this section, we explore the prediction accuracy for a single O-D pair, namely DFW to ATL. This pair was chosen because in concurrent research\textsuperscript{20}, we are exploring a NAS-wide simulation of congestion resulting from forecasted weather impact in Atlanta Air Route Traffic Control Center (ARTCC) (ZTL), and DFW to ATL is an O-D pair predicted to be significantly impacted. The NAS-wide simulation utilizes the actual demand and filed route fractions for August 30, 2010. As such, we will explore the prediction error associated with this O-D pair for this date to gain insight into the model behavior and provide directions for future research.
The DFW to ATL route utilization prediction model captures the historic flow fraction and the filed flow fraction for prediction with weights of 0.330 and 0.670, respectively. Using these weights, the average predicted error and variance for DFW to ATL across all routes and days in the prediction set is 1.10% and 0.12%. The DFW to ATL network is composed of 30 routes, which are displayed in Figure 13. Since the historic fraction coefficient is non-zero for this O-D pair, some amount of flow will be predicted on each route. However, on August 30, 2010, only 4 of these routes have filed flight plans. As such, the average prediction error for this day is slightly higher, at 0.65%; however the variance in the error is lower, at 0.04%.

Figure 14 displays the prediction error for each route on this day, where the red data points correspond to the routes actually utilized. With one exception, the actually flown routes have the highest prediction errors, with an average absolute error of 4%. Table 2 summarizes predicted and actual flow fractions for these four routes.

Examining Table 2, we notice that the four route definitions are composed of highly similar sector strings, where only a sector or two might be different between two routes. Given the similarity between these routes, we compute the overall predicted flow across all 4 routes to be 0.965 as opposed to the total actual flow of 1, resulting in a slightly smaller overall error of 3.4% across the four flows. This implies that over 96% of the flow for this day was captured by the prediction model.

![Figure 13. O-D-R Network for DFW to ATL.](image-url)
As the overall goal of FCM is to accurately predict the traffic flow through NAS resources, another metric of prediction accuracy is the error associated with the total flow in a sector. Examining Figure 14, we see that many of the 30 routes are quite similar. In fact, if we examine the sector-list definition for each route, we find that only 50 distinct sectors are used. By accumulating the flow fractions of all routes that utilize a sector and comparing the predicted and actual sector utilization fractions, we find that the average error across all sectors is 0.99%. Further comparing only the sectors where flows were actually present shows a slightly higher error, 3.2%. Table 3 lists the sectors corresponding to the routes actually utilized and associated predicted flows.

**Table 3. DFW to ATL actual verses predicted sector flow fractions**

<table>
<thead>
<tr>
<th>Sector</th>
<th>Actual Flow Fraction</th>
<th>Predicted Flow Fraction</th>
<th>Absolute Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZFW25</td>
<td>0.35135</td>
<td>0.43033</td>
<td>0.07897</td>
</tr>
<tr>
<td>ZFW52</td>
<td>0.94595</td>
<td>0.88409</td>
<td>0.06185</td>
</tr>
<tr>
<td>ZFW71</td>
<td>1</td>
<td>0.99747</td>
<td>0.00253</td>
</tr>
<tr>
<td>ZFW83</td>
<td>1</td>
<td>0.99937</td>
<td>0.00063</td>
</tr>
<tr>
<td>ZFW92</td>
<td>0.64865</td>
<td>0.56624</td>
<td>0.08241</td>
</tr>
<tr>
<td>ZME43</td>
<td>0.78378</td>
<td>0.77533</td>
<td>0.00846</td>
</tr>
<tr>
<td>ZME45</td>
<td>0.21622</td>
<td>0.22187</td>
<td>0.00565</td>
</tr>
<tr>
<td>ZME46</td>
<td>0.21622</td>
<td>0.22187</td>
<td>0.00565</td>
</tr>
<tr>
<td>ZTL08</td>
<td>0.78378</td>
<td>0.76447</td>
<td>0.01932</td>
</tr>
<tr>
<td>ZTL09</td>
<td>1</td>
<td>0.99122</td>
<td>0.00878</td>
</tr>
<tr>
<td>ZTL10</td>
<td>1</td>
<td>0.98651</td>
<td>0.01349</td>
</tr>
<tr>
<td>ZTL11</td>
<td>1</td>
<td>0.98678</td>
<td>0.01322</td>
</tr>
</tbody>
</table>
3. Summary and continuing research

The initial analysis for the route utilization prediction model revealed that only the historic flow fraction and filed flow fraction were useful for predicting route utilization, and that in many cases only the filed flow fraction has any correlative value. This initial result highlights the need for a day-of prediction model as historic flow fractions are insufficient for capturing the spatial distribution of demand. However, the quality of the predictions provided by the initial model varied greatly across all O-D pairs. Specifically, some O-D pairs had very low prediction errors and variances, showing that the initial model has promise. However, the poor performance of other O-D pairs highlights the need to improve the model by defining an additional metric for prediction.

The analysis of the DFW to ATL network points to such an additional metric. Specifically, the similarity of the routes in the network could be exploited to improve the prediction on a given route. For example, if two routes are similar, previously filed flight plans for one route may correlate with the actual usage of another. Capturing this effect requires defining the similarity between routes, and we’ve identified two potential approaches that we will pursue in future research.

The first approach measures the distance between two routes, where distance will be defined using a string to string comparison, such as that presented by Wagner. Essentially, this approach calculates the number of character (or sector) change operations, to make one string identical to the other. Since each operation can be assigned a different weight and the weights can change based on where in the string the operations occurs, a flexible algorithm for comparing the similarity of routes can be developed. Using this similarity, we can then determine if factors that predict utilization in very similar routes can be used more broadly to improve the prediction accuracy of the model.

Another approach involves exploiting the O-D-R network structure. Briefly, the O-D-R network utilized in FCM can represent NAS resources at varying levels of resolution. Specifically, airports may be clustered together and flows between O-D pairs represent the flows between the airports contained in each cluster. Similarly sectors can be clustered together as ARTCCs and center transits capture all flow between any sectors in each ARTCC. Using this definition, we can map a filed flight plan for a given airport O-D pair to the clustered O-D pair route which may improve the aggregate prediction of flow across the route. By clustering the airports in this manner, we also significantly reduce the computational effort required to perform the above defined regression as fewer O-D parameters need to be computed when the nodes represent clusters of airports. However, additional research will need to be conducted to verify that the cluster-defined weighting factors provide a reasonable approximation of the individual airport O-D pair routing predictions.

VI. Conclusion

A method of predicting aggregate air traffic demand for a real-time queuing network model of the NAS has been proposed. While this work has been done for a specific decision-support concept, it is widely applicable to any aggregate traffic flow model that is to be initialized from real-time traffic management data. Even in the absence of decision support automation, the model could be useful to traffic managers in alleviating the need to retrieve historical traffic information and integrate this knowledge with current traffic to estimate future demand.

Acknowledgements

The authors would like to thank Philip Brown, Daniel Greenbaum, and Harold Nikoue for their invaluable assistance in assembling and reducing the large data sets required for this analysis.

Notice

This work was produced for the U.S. Government under Contract DTFAWA-10-C-00080 and is subject to Federal Aviation Administration Acquisition Management System Clause 3.5-13, Rights In Data-General, Alt. III and Alt. IV (Oct. 1996).

The contents of this material reflect the views of the authors and The MITRE Corporation and do not necessarily reflect the views of the FAA or the DOT. Neither the Federal Aviation Administration nor the Department of Transportation makes any warranty or guarantee, or promise, expressed or implied, concerning the content or accuracy of these views.
References


