[EN-012] Validation of En Route Capacity Model with Peak Counts from the US National Airspace System

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Abstract: Airspace capacity estimates are important for managing air traffic and predicting the effectiveness of new airspace designs and proposed decision support tools. Because air traffic management relies on manual procedures, controller workload determines the traffic limit of most sectors. Current operational procedures for estimating capacity in United States airspace do not account for conflict avoidance and recurring workload. This paper examines a more complete analytical model. Each sector has a capacity determined by the workload intensity of inter-sector coordination, aircraft separation assurance, and repetitive activities. As the total workload intensity approaches unity, the sector reaches capacity. The resulting workload equation is quadratic in traffic count. Its solution provides a simple formula for capacity. In this preliminary study we for the first time determined its parameters by regressing for all sectors in the 20 United States continental centers. We regressed for individual centers and for the overall set of centers. The capacity parameters from the overall regression estimate the *inherent* capacity potential of a sector. The capacity parameters from a center regression estimate the *achieved* operational capacity of the sectors in that center. The inherent capacity differs significantly from the achieved capacity for most centers.

Keywords: airspace, capacity, workload, sector.

1. INTRODUCTION

Airspace capacity estimates are important for managing air traffic and optimizing air traffic procedures. Air traffic managers need accurate estimates of the capacity of current and reconfigured sectors to minimize delay from storms and demand peaks. Capacity estimates are also essential for predicting the effectiveness of new airspace designs [1-3] and the benefits of proposed decision support tools.

Air traffic management relies largely on manual control procedures. Therefore, controller workload determines the operational traffic limit of most sectors [4-9]. The current operational procedure [10] for estimating capacity in the United States National Airspace System (NAS) is useful, but has limitations. It does not explicitly account for workload from conflict avoidance activities and recurring tasks, and it includes a fixed limit that can underestimate the capacity of large sectors.

We have examined a more complete analytical model for en route sector capacity [11-13] that can be adapted to transit time and sector volume changes caused by weather or sector redesign. Each en route air traffic sector has an inherent capacity determined by the queuing workload intensity of background activities, inter-sector coordination, aircraft separation assurance, and repetitive activities such as traffic scanning. The workload intensity associated with each task is the product of the task rate and the mean time required to service the task. The four task types have different occurrence rates and service times. As the sum of the four workload intensity products approaches unity, the sector reaches capacity. The resulting workload equation is quadratic in traffic count, and its solution provides a simple formula for sector capacity.

The formula for workload intensity includes a number of variables that can be estimated from known airspace parameters. However, three of the four task components have at least one unknown parameter. In this study we determine the unknown parameters by fitting the model predictions to observed peak daily counts for 790 en route sectors in the 20 United States continental centers. This is our first attempt to fit the model to data for the entire NAS.

We regress for individual centers and for the overall set of centers. The capacity parameters from the overall regression provide an estimate of the inherent capacity potential of a given sector. The capacity parameters from

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a center regression are more indicative of the achieved operational capacity of the sectors in that center. We examine how the achieved capacity varies from center to center to determine whether a single set of capacity parameters will suffice to fit the capacity model to current NAS operational data.

2. CAPACITY MODEL

Background tasks, such as routine supervisory interactions or equipment checks, produce a constant workload intensity G_b without respect to the aircraft count in the sector. We assume that the background workload is identical for all centers. This implies that observed center-to-center capacity differences are caused by the other workload components, and it allows us to arbitrarily assign G_b a value of 0.1.

Transit tasks associated with inter-sector coordination occur at a rate

$$\lambda_t = N/T, \tag{1}$$

where N is the number of aircraft in the sector, and T is the average transit time through the sector.

Recurring tasks, such as checking route compliance of sector traffic, occur at a rate

$$\lambda_r = N/P. \tag{2}$$

Here P is the mean task recurrence period per aircraft.

Conflict resolution tasks occur when potential aircraft separation violations arise. We calculate the conflict rate for an aircraft by considering the rate at which other aircraft trajectories penetrate its protected airspace [14]. We define κ as the volumetric traffic density along the aircraft's flight path, and M_h and M_v as the horizontal and vertical miss distances that define a separation violation. The aircraft sweeps out a volume $4M_h M_v V_{21}$ of protected airspace per unit time, where V_{21} is the mean of the pair-wise closing speeds between the subject aircraft and all other closing aircraft that could pass within the defined miss distances. If the volumetric traffic density κ is uniform, the conflict rate is

$$\lambda_a = 4\kappa\, M_h\, M_v\, V_{21}. \tag{3}$$

The sector controller is responsible for all aircraft in the sector. If there are N aircraft in the sector each experiencing conflicts at an average rate of λ_a, then the total conflict rate for all aircraft is $N\lambda_a$. At practical traffic densities, very few of these conflicts involve more than two aircraft. Thus, the rate of conflicts [15] seen by the sector controller is approximately

$$\lambda_c = N\lambda_a/2. \tag{4}$$

If Q is the sector volume, the density of aircraft in the sector is

$$\kappa = N/Q, \tag{5}$$

and the sector conflict rate is approximately

$$\lambda_c = (2\, N^2/Q)\, M_h\, M_v\, V_{21}. \tag{6}$$

Although we do not know the magnitude of the mean relative velocity, we can estimate it by regression.

When all aircraft in a sector cruise at constant altitude, the vertical miss distance that determines loss of separation is constant. In sectors in which aircraft routinely change altitude we increase the vertical miss distance to reflect the resulting increase in altitude uncertainty. We increase the vertical miss distance from its nominal value of 1000 ft to a maximum value M_{vmax} that is proportionally to F_{ca}, the daily fraction of sector aircraft that change altitude by more than 2000 ft.

When all aircraft in the sector change altitude, Fca = 1 and the vertical miss distance is M_{vmax}. When Fca < 1, the vertical miss distance is

$$Mv = 1000 + Fca\,(M_{vmax} - 1000). \tag{7}$$

Regression over all 20 centers gives an M_{vmax} of approximately 1600 ft.

The complete equation for workload intensity G is

$$G = G_b + \tau_t\lambda_t + \tau_r\lambda_r + \tau_c\lambda_c, \tag{7}$$

where τ_t, τ_r, and τ_c are the mean service times for transit, recurring, and conflict tasks. When total workload intensity G exceeds 0.8, Schmidt [4] determined that safety begins to degrade. That intensity limit defines the sector capacity.

3. REGRESSION

3.1 Regression Unknowns

The capacity equation includes four unknown factors. The first is τ_t, the transit service time. The second unknown factor involves recurrence parameters. Because we do not know the magnitude of the recurrence period P, we perform the regression for recurring workload by fitting the dimensionless product τ_r/P, which is the fraction of total time devoted to recurring tasks for each aircraft. The third unknown is the product of conflict service time τ_c and relative mean relative closing velocity V_{21}. We call this product d. It has dimensions of distance and represents the mean separation lost while resolving each conflict. The NAS regression value of this "conflict distance" is about two nautical miles. The fourth unknown is the maximum vertical miss distance M_{vmax}.

To speed the regression process we use scale factors to quantize each of these variables as integers. The resolution of transit service time τ_t is one second. The resolution of the dimensionless recurring workload factor τ_r/P is 0.1. The resolution of the conflict distance d is 0.1 nautical mile. The resolution of M_{vmax} is 200 ft.

3.2 Regression Data Sources

We determine the unknowns by fitting the model's capacity predictions to observed peak daily counts for each of 790 sectors in the 20 U.S. continental Air Route Traffic Control Centers (ARTCC). We obtained historical summaries of peak traffic counts and sector transit times from the Federal Aviation Administration (FAA) Performance Data Analysis Reporting System (PDARS) [16] and the FAA Sector Design and Analysis Tool (SDAT) [17]. We obtained sector airspace definitions and aircraft altitude information from SDAT.

Most of the peak counts we used were from days in July and August of 2007. We regressed system-wide and center-wide for all sectors in the 20 NAS continental centers. The system-wide regression included one peak count for each sector in the NAS. That count came from the day with the highest overall operations count in this period. Each center-wide regression included ten peak counts for each of the sectors in the center. Those counts came from the ten days with the highest overall operations counts in this period.

We use the system-wide regression to determine the sensitivity of effective miss distance to the altitude change fraction of each sector.

The regression data sources also provide information that allows us to determine the mean sector transit times that are key determinants of transit workload. Air traffic managers currently use historical mean sector transit times to derive a Monitor Alert Parameter (MAP) which warns against operational sector overload. Although decision support algorithms could dynamically predict transit times with accuracy from flight plans and surveillance tracks in real-time simulations and operational situations [1,2], MAP transit times are essentially static. To derive a nominal value for sector capacity, the MAP algorithm uses a fixed value of transit time for each sector. The rule used to calculate the MAP traffic count is constrained by FAA Order 7210.3 [10] to apply uniformly to all sectors in the NAS. It includes a nominal upper limit of 18 aircraft per sector. However, to account for local conditions, air traffic managers are authorized to manually adjust nominal MAP counts by plus or minus three aircraft.

When we regress our capacity algorithm against historical data, we estimate transit workload for each sector from the mean aircraft transit time of all aircraft present in the sector at the time of the observed traffic peak. PDARS and SDAT derive sector boundary crossing times from inter-sector coordination hand-off logs. Those boundary crossing times have one-second resolution, which provides dynamic sector count data and allows us to compute the mean transit time for the sector aircraft at the time of each peak traffic event.

3.3 Regression Objective Function

The model provides a capacity bound. Regressing to fit a bound requires an asymmetric objective function. Our objective function is a simple rule designed to maximize the score of the capacity fit to the observed traffic peaks. It penalizes the fit if the actual traffic count significantly exceeds the model prediction. It does not penalize low traffic counts that might be caused by lack of demand or other factors unrelated to workload. The objective function also reduces the regression influence of extreme outliers, that is, occasional high peak counts that result from brief traffic overloads made possible by temporary increases in controller workforce or other unusual factors.

Fig. 1 illustrates the objective function. It is based on integer peak daily counts and rounded model capacity bounds. It assigns a score of zero to any sector whose capacity bound exceeds its peak daily count by five or more aircraft. The score grows to +5 for a sector whose capacity bound equals its peak daily count or exceeds its peak daily count by one aircraft.

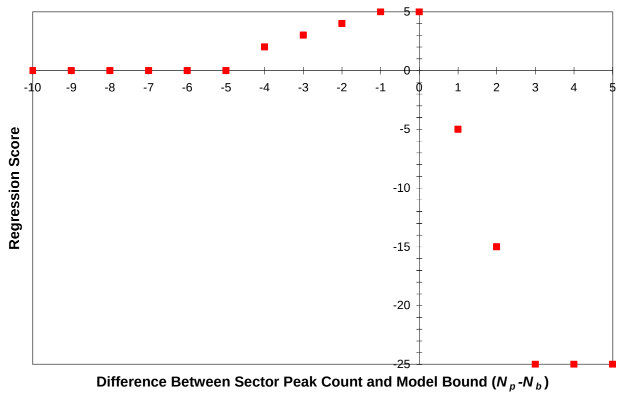

Figure 1. Regression Objective function.

The rule penalizes sectors with peak counts that exceed the capacity bound. The rule assigns a cost of -5 to a sector with a count one aircraft above the bound. The rule assigns a cost of -15 to a sector whose peak aircraft count exceeds the bound by two aircraft. The rule assigns a cost of -25 to a sector whose peak aircraft count exceeds the bound by more than two aircraft. The rule limits the cost to -25 to reduce the regression influence of extreme outliers.

3.4 Regression Algorithm

The use of integer search variables and the relatively narrow range of operationally feasible values for those variables allow us to use a simple exhaustive search algorithm. The data sets were sufficiently large to provide unique objective function maxima.

4. RESULTS

4.1 Comparison of Center Peak Counts

One of the objectives of this study is to determine the minimum number of variables needed to accurately predict the capacity of every en route sector. (Recall that the MAP algorithm uses only a single variable, the historical mean transit time for each sector.)

Peak daily sector traffic counts for the 20 NAS centers show significant center-to-center differences, both in their peak counts and in the distributions of their sector volumes. These large differences indicate that more than one variable will be needed to accurately fit the capacity model to the data.

Centers with busy airports have small sectors with high traffic densities, and exhibit clearly-bounded peak traffic contours. Centers with large airspace volumes over oceanic or sparsely populated regions tend to have large sectors with low traffic densities, and indistinct traffic contours. Fig. 2 illustrates this by contrasting the peak-count versus sector-volume profile of the Washington DC Center (ZDC) with that of the Miami Center (ZMA), which has a large volume of oceanic airspace. For clarity, the chart only includes results for sectors less than 80,000 cubic nautical miles in volume.

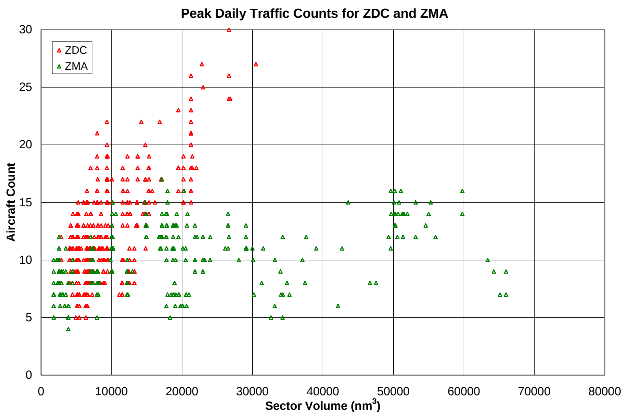

Figure 2. Comparison of peak daily en route sector counts in Washington and Miami Centers.

Although some sectors in these two centers have similar airspace parameters and thus should have similar intrinsic capacities, many ZDC sectors routinely peak near capacity, while many ZMA sectors never reach their intrinsic capacity because of low demand. As a result, capacity parameters regressed from ZDC peak traffic differ significantly from parameters based on ZMA traffic.

4.2 System-Wide Regression results

Fig. 3 shows the capacity estimates resulting from the NAS system-wide regression. This chart also restricts results to sectors smaller than 80,000 cubic nautical miles. It plots the model estimate of capacity and the observed peak daily traffic count versus sector volume for each NAS sector. The scatter in the capacities for sectors with nearly identical airspace volumes results mainly from sector transit time variations, which are related to the length of the sector in the direction of its principal flight routes.

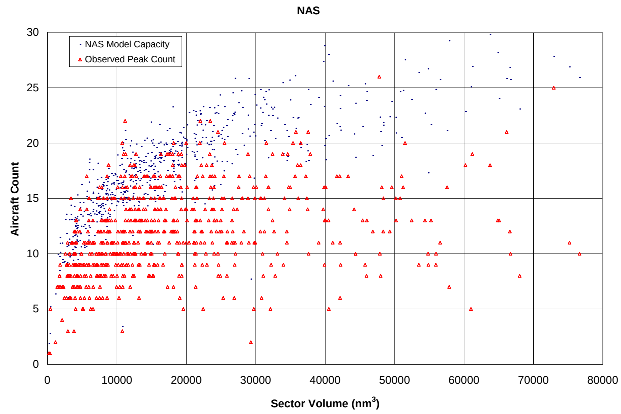

Figure 3. Peak counts and model capacities for NAS sectors.

Fig. 4 comprises the same data as Fig. 3, but directly plots the model capacities against the observed peak sector traffic counts.

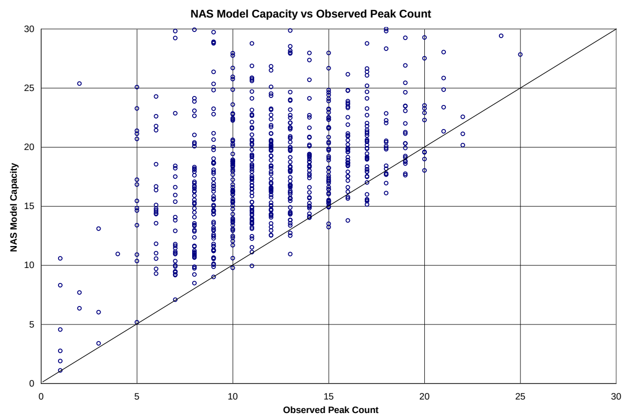

Figure 4. Peak count versus model capacity for NAS sectors.

Low traffic demand and other factors cause most sectors to peak at densities below capacity. The "frontier" trend for maximum count is consistent with the model.

4.3 Center Regression Results

Any study based on the current operational capacity of the sectors in a specific center is best based on regression parameters resulting from analysis of that center.

We evaluated the model capacity for each center using both NAS regression parameters and center regression parameters. The NAS regression parameters provide an estimate of the *inherent* capacity of the sectors in the center. The local center regression parameters provide an estimate of the *achieved* operational capacity of the sectors in the center. For most centers, the inherent and achieved regression parameters differ significantly.

We define the overall capacity of a center as the sum of the model capacities of its sectors. Overall inherent capacity is based on the NAS regression, and overall achieved capacity is based on the center regression.

The overall inherent capacity for every one of the 20 NAS centers is larger than its overall achieved capacity. This is to be expected because the asymmetrical objective function fits the model to the busiest sectors in the NAS.

Overall achieved capacity is closer to overall inherent capacity for centers with smaller sectors because small sectors tend to be more constrained by workload than lack of demand. Furthermore, the MAP rule does not limit most small sectors since it usually exceeds their observed peak counts.

Large sectors contribute less to the regression score. Their inherent capacity tends to be an extrapolation of small sector capacity. The operational limit of the MAP rule and lack of demand combine to limit the peak observed counts in most large sectors. Most large sectors could handle peak traffic that exceeds current procedural limits, and the NAS regression provides a truer indication of their inherent capacity.

Small sectors are more prevalent in centers with busy airports where additional controllers are needed to handle dense traffic. Boston, Washington, and Atlanta are the only centers whose achieved capacities approach their inherent capacities. Furthermore, the Boston and Washington local capacity model parameters closely approximate those of the NAS capacity model. The individual capacity parameters resulting from the Atlanta regression differ from those of the NAS regression, but they combine to keep Atlanta's achieved capacity close to its inherent capacity.

The Seattle Center (ZSE) is an extreme example of the tendency of the local regression to under-estimate the capacity of large sectors. Fig. 5 compares the individual ZSE sector capacity estimates resulting from the NAS regression with those from the local center regression. It also shows the observed peak count N_p for each ZSE sector day.

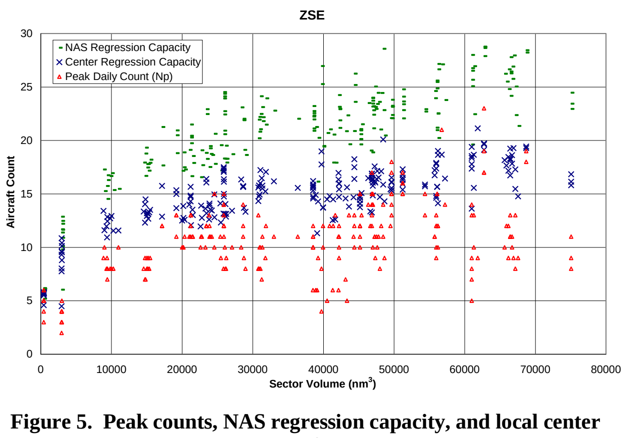

Figure 5. Peak counts, NAS regression capacity, and local center regression capacity for Seattle Center.

Most ZSE sectors have low demand relative to similar sectors in other centers. The achieved regression capacities of the larger ZSE sectors are typically five or more aircraft below their inherent capacities.

4.4 Normalized Capacity Density of Centers

The notion of overall achieved capacity by itself is not sufficient to compare the capacity characteristics of air traffic control centers. A meaningful capacity comparison must normalize for differences in center size and sector count. The *normalized capacity density* of a center is essentially its mean achieved traffic density per sector. Specifically, it is the sum of the local achieved model capacities for all sectors in the center, divided by its total airspace volume (in units of 10,000 cubic nautical miles), and divided by the number of sectors in the center.

Fig. 6 sorts the 20 centers (and the NAS as a whole) by this measure. Normalized capacity density is lowest in centers where large sectors serve mainly oceanic or sparse population areas. It is highest where many small sectors serve major airports. The normalized capacity density of the NAS as a whole is 0.15. (The NAS metric uses the same formula as the center metric, multiplied by 20 to account for its center count.)

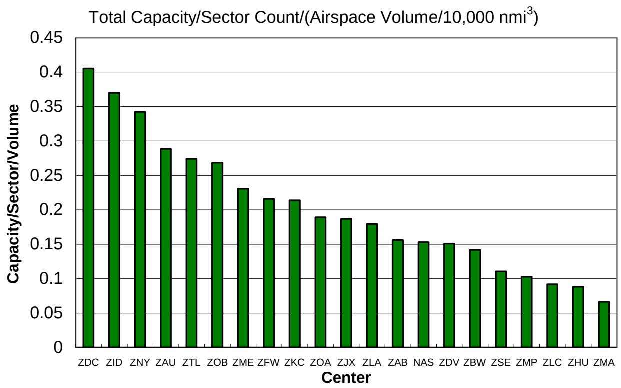

Figure 6. Centers sorted by normalized capacity density.

The range of this metric is indicative of the large variation in current operational requirements among the 20 NAS centers. Low normalized capacity density is not an indicator of inferior performance. Centers with low normalized capacity density are, by definition, characterized by low demand and large airspace volumes. International boundaries and center boundaries often constrain the designs of their large sectors. Additional constraints include surveillance coverage limitations, special use airspace, and the MAP limit itself. Centers with high normalized capacity density tend to include many active routes serving major hubs or multiple busy airports. High traffic density forces them to employ small sectors, and small sectors allow them to organize their operations and design their airspace with more freedom from the large-sector constraints listed above.

The uneven distribution of traffic is evidenced by the fact that the highest normalized capacity density for a center (0.41 aircraft in 10,000 cubic nautical miles for ZDC) is significantly less than the peak traffic density of many busy NAS sectors. For example, the peak traffic density handled by sector ZDC32 is 20 aircraft in 10,000 cubic nautical miles, about fifty times the normalized capacity density of ZDC as a whole.

5. CONCLUSIONS

This paper continues an on-going examination of a simple analytical model for the capacity of en route air traffic control sectors. Each sector has a capacity determined by the workload intensity of inter-sector coordination, aircraft separation assurance, and repetitive activities.

This is our first application of the model to the entire NAS. We determined the unknown parameters of the model by regressing its capacity predictions against FAA instantaneous count reports for 790 sectors in the 20 United States continental centers. We based the center regressions on data from ten busy days for each sector.

Most of the peak counts were from days in July and August of 2007. We regressed system-wide and center-wide. The system-wide regression included a peak count from the day with the highest overall operations count in the period for each sector in the NAS. Each center-wide regression included peak counts for each of the sectors in the center from the ten days with the highest overall operations counts in this period.

The results are informative. The peak count data reflect the wide range of complexity, demand, and airspace characteristics of the NAS. The capacity parameters derived from the NAS-wide regression provide an estimate of the *inherent* capacity potential of NAS sectors. The capacity parameters derived from the center regressions estimate the current operational *achieved* capacity of each center. The achieved capacity varies significantly from center to center, and the achieved capacity for a typical center is significantly less than its inherent capacity.

These large center-to-center differences indicate that a single set of fixed capacity parameters will not suffice to fit the capacity model to current NAS operational data. Individual adaptation to each center will be necessary.

6. ACKNOWLEDGMENT

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