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Refinements to a Procedure for Estimating Airfield Capacity

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ABSTRACT

This paper presents a method for obtaining airfield capacity estimates, using historical data from the Federal Aviation Administration's Aviation Systems Performance Metrics (ASPM) database. The process first involves merging individual flights and quarter-hour airport runway operations datasets from ASPM to create a new dataset. Data for Newark International Airport and San Diego International Airport from 2006 to 2011 was used. Secondly, filters for meteorological condition, runway configuration, called rates, and fleet mix were applied to the two airport datasets. The filtered datasets were then used in a censored regression model of capacity that includes queue length (number of aircraft waiting to arrive/depart) and arrival/departure throughput count splits as independent variables. These attributes were found to impact airfield capacity at statistically significant levels, and parameters had expected signs and magnitudes. Additionally, capacities under ideal conditions were found to be reasonably close to other sources. The model also confirmed that average capacities at EWR during hours when a Ground Delay Program (GDP) was running were lower than when there was no GDP in effect. The method described in this paper can be used to more precisely quantify airfield capacities in specific conditions of particular interest to air traffic controllers and airport operators, to better facilitate decisions that rely heavily on a good understanding of capacity in these conditions. The data exploration and preparation undertaken as part of the study reveals some of the finer points of the ASPM data and how it can be used in a more meaningful way for airfield capacity estimation.

INTRODUCTION

Reliable airfield capacity estimates are critical for effective planning and operations in a capacity-constrained aviation system. As a result, airfield, and individual runway, capacity estimation has received much attention in both the research and practice since the early 1970s (*1*). Techniques for airfield capacity estimation include analytic modeling (*2*, *3*), statistical estimation (*4*, *5*), and various types of simulation modeling (e.g., SIMMOD, *runway*Simulator). Statistical models are particularly useful for facilitating comparisons and validation of capacity estimates from the other two approaches. Because they are based on actual data from airports under specific weather and operational (and other) conditions, the results can be used to assess how well analytic and simulation models perform under particular conditions at a subject airport (*6*). In addition, analytic models account for the main factors that affect capacity at all airports (such as configuration, weather, etc.) in the same manner, and do not tailor their treatment of these factors at each particular airport. Statistical models such as the one presented in this paper are able to do so.

The objective of this paper is to present an empirical method for obtaining airfield capacity estimates, using historical data from the Federal Aviation Administration's (FAA) Aviation Systems Performance Metrics (ASPM) database. The process involves 1) merging datasets of individual flights and quarter-hour airport runway operations from ASPM to create a new dataset, 2) applying filters to the data, and 3) applying a new econometric model specification. The econometric model was originally developed by Hansen (*4*) to assess the impacts of a new runway at Detroit-Wayne County Airport. It has since been used to compare capacity estimates from the *runway*Simulator model and the Airfield Capacity Model (ACM) (*6*), as well as assess estimates from *runway*Simulator (*7*). The model employs censored regression in order to capture some critical features of airport runway capacity. Firstly, capacity can vary significantly from one time period to the next due to many influencing factors. We attempt to control for the most significant factors (*8*) through data filtering and specification of an econometric model. Secondly, capacity cannot always be directly observed from airfield throughput count data, because there are low demand periods of the day when available capacity is underutilized. The modeling procedure developed here is a refinement of the procedure developed as part of ACRP Project 03-17 (*7*). Refinements include modification to the regression model specification, and changes to the process of preparing, filtering, inputting data to the regression model.

ASPM data for Newark Liberty International Airport (EWR) and San Diego International Airport (SAN) were obtained for this study. The following section provides a description of the analysis that was undertaken to understand the information in the datasets, in preparation for the filtering process and the censored regression model. After filtering for meteorological condition, runway configuration, called rates, and fleet mix, it was found that arrival/departure throughput count splits and queue lengths had statistically significant impacts on airfield capacity. Please note that by "queue length" we mean the total number of aircraft that are ready and waiting to use a runway for arrival or departure. As such, by "queue" we refer to a virtual rather than a physical queue, although an arrival queue may certainly include those aircraft queued at a runway.

This study adds to the body of literature on airfield capacity estimation with two contributions. Firstly, the procedure can be used to more precisely quantify airfield capacities in specific conditions of particular interest to air traffic controllers and airport operators, to better facilitate decisions that rely heavily on a good understanding of capacity in these conditions. Secondly, the data exploration and preparation undertaken as part of the study highlights some of the finer points of the ASPM data, and how it can be used in a more meaningful way for airfield capacity estimation.

It will be noted here that "throughput count" refers to the number of aircraft operations (arrivals + departures, unless otherwise stated) that were accommodated by the airfield over a period of time. From this point forward, aircraft "throughput count" will simply be called "count".

DATA PREPARATION

The Aviation System Performance Metrics (ASPM) database is part of the FAA Operations and Performance Data system, available at https://aspm.faa.gov/. ASPM contains extensive operational data for 77 major US airports. Two datasets from the "Download/Airport" section of the database, which can be accessed with permission from the FAA, were used in this work. The first dataset consists of quarter-hourly aircraft arrival and departure counts, demands, called rates, delay metrics, meteorological conditions information, runway configurations, and other airport data. The second dataset consists of detailed operational information for individual flights. Data files for Newark Liberty International Airport (EWR) and San Diego International Airport (SAN) for August 1, 2006 through July 31, 2011 were obtained. EWR was chosen for analysis because it is one of the busiest airports in the U.S., where demand is at or near capacity during peak hours; however, it can also have periods that are less busy. EWR has two parallel runways that are intersected by a third runway, and includes aircraft taxiing across runways. SAN is also a very busy airport, partly due to the fact that it only has one runway. SAN further differs from EWR in that Ground Delay Programs (GDPs) are rarely instituted there, whereas at EWR they are a more common occurrence, particularly in the summer months.

We constructed a final quarter-hourly dataset (herein referred to as "final dataset") by combining information from these two ASPM files. This final dataset includes the following information for each quarter-hour interval:

1. Date and time (characterized by year, month, date, hour and quarter)
2. Aircraft counts, for both arrivals and departures
3. "New" demands, arrivals and departures
4. Total ("new" plus queued) demands, arrivals and departures
5. Called rates – Airport Arrival Rate (AAR) and Airport Departure Rate (ADR)
6. Aircraft fleet mix (Small, Large, B757, Heavy), arrivals and departures
7. Ceiling and visibility
8. Meteorological condition (determined from ceiling and visibility data)
9. Wind angle and wind speed
10. Runway configuration

The quarter-hour ASPM file contains fields for all the above except aircraft fleet mix. As a result, for the final dataset, arrival and departure fleet mixes for each quarter-hour were calculated from the individual flights file, based on the actual quarter-hour in which an aircraft was recorded to have arrived or departed the subject airport. Eventually, aircraft count and demands (items 2-4) were also sourced from the individual flights file, in order to ensure that these metrics are as close a reflection of actual operations as possible. Count and demands in the quarter-hour ASPM file are enumerated for the purposes of accounting and reporting delay statistics, and may not quite reflect the information we require for our modeling purposes.

For counts, we originally used the arrival and departure count for efficiency computation ("EffArr" and "EffDep" fields) from the quarter-hour file. These were replaced with the "Actual Wheels On" and "Actual Wheels Off" fields from the individual flights file, respectively. When the two sets of counts were compared for EWR from August through December 2006, it was found that 69% and 76% quarter-hours had perfect matches for arrivals and departures, respectively (and about 95-98% of quarter-hours matching within ± 1 count).

It was determined that the demand counts in the ASPM quarter-hour file ("ArrDemand" and "DepDemand") are constructed such that delays due to GDP are accounted for and attributed to the airport at which the GDP was called. It is described in the FAA's ASPM Airport Quarter Hour Data Dictionary as the "number of aircraft intending to depart (arrive) for the period". To illustrate, in the quarter-hour ASPM dataset, arrival demands at an airport are constructed as follows: the start of arrival demand for a flight is calculated by adding its filed en-route time to its wheels-off time at the departure airport, and subtracting ground delay time imposed on this flight at the departure airport due to a GDP or ground stop at the (arrival) airport. Therefore, that flight's contribution to arrival demand begins before it actually arrives in the terminal airspace, in order to properly attribute GDP delays to the airport where the GDP is taking place. The start of departure demand for a flight is calculated by adding a flight's unimpeded taxi-out time and any ground delay time to its filed gate-out time. The departure demand is adjusted such that ground delay imposed on a departing flight (due to problems at the destination airport) is not attributed to the departure airport.

To summarize, a flight will contribute to demand starting in the time interval it was first filed to arrive/depart, until the time interval it actually does, adjusting for ground delay appropriately. Clearly this does not reflect the "actual" operational aircraft demand that controllers are working to safely accommodate on the runways, which we require for capacity analysis. As a result, for this research we also constructed demand metrics from the individual flights file, which better reflect actual operational demand. Arrival demands were constructed by adding flight plan estimated en-route time ("FPETE") to actual take off time at the origin airport ("ActOffSec"). A shortcoming of this demand calculation is that en route delays incurred due to TMIs (Traffic Management Initiatives) are not adjusted for. Departure demands were calculated by adding actual gate out time ("ActOutSec") to unimpeded taxi out time ("NomTO").

Note that the demand metrics constructed above are what we term "new" demands – from the above information alone, we can determine the first quarter-hour in which a flight requested service. However, the total demand in each quarter-hour can include flights queued (unserved and waiting) from previous quarter-hour periods in addition to the flights first requesting service in the present quarter-hour. Total demand can be calculated from the "new" demands and counts. In addition, if a flight arrives or departs earlier than the quarter-hour period it was expected to have demanded service, the flight is recorded as demand only in the quarter-hour in which it was served. Our calculated demand is equivalent to "ArrDemand" and "DepDemand" in the ASPM quarter-hour file, insofar as they reflect "queued" + "new" demands.

METHODOLOGY

The section describes the data filtering steps and the capacity model development.

Data Filtering

The constructed quarter-hour dataset was further aggregated into hours and filtered by meteorological condition, runway configuration, called rates and fleet mix. The purpose of filtering is to explicitly control for factors that are well understood to affect capacity. The filtering steps are described below, and the process is illustrated using EWR as an example.

Meteorological Condition

The hourly data was first sorted by meteorological condition – Visual Meteorological Condition (VMC), Marginal VMC (MVMC), or Instrument Meteorological Condition (IMC). The entire hour must have operated under the designated condition to be included in the filter. Meteorological condition is among the most significant factors to impact airfield capacity both directly and indirectly (*8*). It impacts capacity directly through aircraft separation requirements and pilots' use of instruments. Indirectly, it dictates which runway configuration is to be used.

Runway Configuration

Runway configurations also have a significant impact on airfield capacity; the capacities associated with different runway configurations at an airport can vary considerably (*8*). Each dataset was further filtered to only include hours where the prevailing runway configuration for a given meteorological condition was in use. At EWR, the prevailing configurations were found to be 22L|22R (22L for arrivals and 22R for departures) in VMC, and 4R|4L in IMC.

Called Rates

The data was further filtered based on the criteria that the sum of the Airport Arrival Rate (AAR) and Airport Departure Rate (ADR) was within the normal range observed over the dataset (August 2006 – July 2011). This filter eliminates observations for atypical circumstances to which air traffic controllers responded by raising or lowering the AAR and ADR to unusually high or low values. These circumstances could include non-functioning navigational aids, adverse terminal area weather, configuration transition periods, reduced staffing in the control tower, and others. Because these circumstances will not be accounted for as independent variables in the capacity model, we eliminate their impacts on capacity through this filter.

Figure 1 shows a histogram of the total called rate (AAR+ADR) per quarter-hour period at EWR, operating under VMC and runway configuration 22L|22R. About 98% of the total called rates were between 18 and 24 operations per quarter-hour. As such, only quarter-hours with rates between 18 and 24 are included.

Fleet Mix

Minimum separations are required between consecutive aircraft on the runway and in the terminal airspace, and these separations are dictated by the size category each aircraft falls into (Small, Large, B757, and Heavy) and the sequence of aircraft. In addition, fleet mixes at a major airport can vary widely although there is daily consistency due to established airline schedules. Although we do not control for aircraft arrival and departure sequences, we do aim to obtain a subset of data with a relatively consistent fleet mix profile, using cluster analysis.

Cluster analysis is used to identify similar groups within a larger set of observations. Members of a group should be highly similar to one another, with respect to certain selected characteristics of interest, in comparison to members of another. Ward's minimum variance method was chosen among the candidate hierarchical clustering methods that could be employed for this analysis. Each observation starts as its own cluster, and is then paired up with another that is most similar such that they are combined into a single cluster. This combining of clusters continues, by minimizing the within-cluster sum of squares at each step.

We determine the appropriate number of fleet mix profile clusters that should be obtained using the pseudo-F statistic and the cubic clustering criterion (CCC). The appropriate number of clusters is that for which the pseudo-F statistic and the CCC are maximized; however, in cases where a local maximum is not observed for either criterion, judgment should be exercised in choosing the number of clusters. The data in the cluster with the highest number of observations is then chosen for input to the capacity model.

For EWR operating in VMC, with runway configuration 22L|22R and total called rate (AAR+ADR) between 18-24 ops per quarter hour, the appropriate number of clusters was found to be 5 (see Table 1). Of these 5 clusters, the first set was chosen as it had the highest number of observations and group members were visually observed to exhibit relatively smaller variances in their attributes. The observations in this subset were used as inputs to the capacity model.

Capacity model

A censored regression model was used to estimate airfield capacity from the prepared datasets. The model was constructed to capture some critical features of capacity. Firstly, capacity is a random variable that can vary significantly from one time period to the next, due to the many factors that can influence it (the most important of which we explicitly controlled for through the filtering process). Secondly, we assume that capacity can increase with queue lengths, up to a maximum value that is reached only when queues for service are very large. Thirdly, we assume that capacity is largest when arrival and departure aircraft are served with equal priority, decreasing as one movement type takes priority over the other (*7*). Finally, an observed count reflects the smaller of demand or capacity. When demands exceed capacity, the count reflects capacity. However, when capacity exceeds demand, the count reflects demand rather than capacity. A censored regression model assumes that the dependent variable (capacity) is a latent variable – censored, as it cannot be observed beyond a maximum threshold value (demand) (*9*). Censored regression estimates how (observable) independent variables impact capacity rather than throughput count.

As described above, we observe that two situations can arise (*4*):

$$Q_t = \begin{cases} C_t, & if \quad 0 < C_t < D_t \\ D_t, & if \quad\quad C_t \geq D_t \end{cases} \tag{1}$$

Where

Q_t is aircraft count, or "observed" capacity in hour t,

C_t is capacity in t, and

D_t is demand (or upper bound of observable capacity) in t.

When the demand exceeds count, capacity is equated to the count. When count equals demand, capacity will equal or exceed demand due to the censoring effect.

The regression model is specified as follows:

$$\log(Q_t) = \min[\log(C_t), \log(D_t)] \tag{2}$$

$$\log(C_t) = \alpha + \beta\left(1 - \frac{\min(x_t, x^*)}{x^*}\right) + \gamma_1 \max[0, M_t - 0.5] + \gamma_2 \max[0, 0.5 - M_t] + \varepsilon \tag{3}$$

Where

$\alpha, \beta, \gamma_1, \gamma_2$ and σ^2 are estimated parameters,

x_t is the total number of aircraft in both the arrival and departure queues in hour t,

x^* is the 95th percentile value of x_t,

M_t is the arrival count divided by total count in t, and

ε is an independent and identically distributed error term, normally distributed with mean 0 and variance σ^2.

Recall that this model is applied to data that has been filtered by meteorological condition, runway configuration, commonly observed called rates, and fleet mix.

It is expected that under ideal conditions – when the second, third, and fourth terms of Equation (3) are zero – α reflects a maximum capacity such that $C_t = e^{\alpha}$. The parameter β captures the impact of queue lengths on capacity; Figure 2 shows the relationship between queue length and count for the filtered EWR VMC dataset. It can be observed that as queues increase, average count increases up to a maximum value (represented by black bubbles). The size of each black bubble indicates the number of data represented by the one point. The red s-curve represents percentiles; it can be observed that the 95th percentile queue is about 87 ops/hr. As queues reach 87 ops/hr, average count values have flattened out, and we say that maximum capacity is reached at this point, hence the choice of x^*. When $x < x^*$, maximum capacity may not be obtained. As a result, the parameter β is expected to be negative.

Parameters γ_1 and γ_2 capture how arrival/departure count splits impact capacity. Capacity is typically largest when the aircraft count mix is approximately even (*7*); this is confirmed in Figure 3 for the EWR VMC filtered dataset. Aircraft count (noting that it is a censored representation of capacity) is highest when arrival/departure splits are even ($M_t = 0.5$). Given the general trends of the arrival, departure and total count data observed in the figure, parameters γ_1 and γ_2 are expected to be negative, as they capture capacity losses due to counts becoming either arrivals or departures heavy.

Model parameters are estimated using maximum likelihood estimation (MLE).

RESULTS

Data from August 1, 2006 through July 31, 2011 at EWR and SAN were run through the filtering process described in the previous section, to result in the following four cases:

The centroids of the predominant fleet mix cluster are similar in VMC and IMC at both EWR and SAN. It can be observed that there are far more observations at SAN in VMC. SAN is very often operating in VMC conditions, such that arrivals and departures are both accommodated on runway 27 and the quarter hour AAR+ADR is 12.

Estimation results for each of the four scenarios shown in Table 2 are contained in Table 3. All parameters have expected signs, and the t-statistics indicate that they are highly significant. The values of α indicate capacity when all other terms are 0; for instance, $\alpha = 4.49$ for EWR in VMC indicates that capacity is 89 ops/hour when all other terms are 0. A negative β value indicates that as queue lengths increase towards the threshold queue length (x^*), so does capacity. In scenarios with a more negative (smaller) value of β, queue lengths have a greater impact on capacity. In other words, it indicates that shorter queue lengths (compared to the 95th percentile queue, or x^*) will cause larger capacity reductions compared to situations where β are larger (closer to zero). It is observed that VMC capacities at both airports are more sensitive to queue lengths than IMC capacities.

Both γ_1 and γ_2 are negative in all cases, indicating that capacity decreases as arrival/departure count split becomes more uneven. At EWR under VMC, when the arrival/departure split becomes heavily favored towards departures (such that $M_t \rightarrow 0$), the capacity reduces at a higher rate compared to when the split is heavily favored towards arrivals ($M_t \rightarrow 1$). At EWR under IMC, the capacity decrease at similar rates whether arrivals or departures are being favored. Under both VMC and IMC at SAN, capacity reduces at a higher rate as the split favors arrivals. The differences between EWR and SAN may be due to the runway configurations predominantly used at each airport.

The last column reports capacities under "ideal" conditions – that is, when all terms in Equation (3) other than the first (α) are zero. Under these conditions, the queue length has reached the threshold queue length x^* and arrival/departure split is even. Therefore, as mentioned above, $C_t = e^{\alpha}$. Capacities at both EWR and SAN are greater in VMC conditions, and appear to be fairly reasonable when compared to those found in ACRP Report 79 (*7*) and the 2004 Airport Capacity Benchmark Report (*10*). As an additional point of comparison, peak hour caps at EWR were set to 83 operations/hour in 2008.

Additional data indicating the hours when GDPs were in effect at EWR in 2006 was also available for this study. As a result, we tested the inclusion of a dummy variable in the capacity model (Equation 3), which took a value of 1 during the hours that a GDP was in effect, and 0 otherwise. This model was applied to a subset of the original ASPM quarter-hour dataset. It should be noted that the predominant runway configurations in use at EWR during IMC in 2006 were 11,22L|22R and 22L|22R. All model parameters, including the GDP dummy variable, were found to be statistically significant.

The results confirm that hourly airfield capacity is lower when a GDP is in effect. It also appears that a GDP has a greater impact on VMC capacities. In 2006, a GDP may have been in place at EWR for any number of reasons, including adverse terminal weather (in which case, the runways would likely operate in IMC), adverse conditions en route to the airport (summer thunderstorms in the airspace over the Midwest, or congestion in the New York airspace, for instance), and other situations that would cause controllers to foresee a drop in capacity. Therefore, the airport may have been operating under a GDP even during times when there were no capacity issues at the airport itself. Because the GDP capacities include all the above instances, this could explain why GDP capacities in Table 4 are not significantly lower than the non-GDP capacities. In addition, it can be observed that IMC capacities are comparable to VMC capacities when the same configuration is in use. Although not shown above, IMC capacities are lower when 4R|4L is in use.

DISCUSSION

This paper has described an empirical method for obtaining airfield capacity estimates, using historical data from the FAA's Aviation Systems Performance Metrics (ASPM) dataset. It is a refinement of the procedure developed as part of ACRP Project 03-17 (*7*). This method can be used to more precisely quantify airfield capacities in specific conditions of particular interest to air traffic controllers and airport operators, to better facilitate decisions that rely heavily on a good understanding of capacity in these conditions. In addition, the data exploration and preparation undertaken as part of the study highlights some of the finer points of the ASPM data, and how it can be used in a more meaningful way for airfield capacity estimation.

The process requires merging of individual flights and quarter-hour airport runway operations datasets from ASPM to create a new dataset, applying filters to this dataset, and applying a censored regression model. After filtering for meteorological condition, runway configuration, called rates, and fleet mix, two independent variables – arrival/departure count split and queue lengths – were included in the censored regression model. Data for Newark International Airport (EWR) and San Diego International Airport (SAN) was used. The resulting parameters for the four scenarios tested had expected signs and reasonable magnitudes, and were statistically significant. Additionally, the capacity for each scenario under ideal conditions (where arrival/departure split is about even and queue lengths equal or exceed a threshold value) were also found to be reasonable. This paper also presented a preliminary analysis of how GDPs impacted capacities at EWR; in future work it is recommended that further attention be given to model specification, as well as investigating which ASPM data would provide the most meaningful results. Also, given that it is unclear from the data how and when any TMI impacts flights and therefore, operational demand, the anomalous delays method developed in Hansen (*4*) could be applied to explore this. Finally, the data analysis method outlined in this paper should be applied to other airports in the NAS to better assess its quality.

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TABLE 1 Fleet Mix Clusters, EWR VMC 22L | 22R

Cluster	Frequency	S	L	B757	H
1	2043	0.01	0.74	0.14	0.11
2	1659	0.01	0.81	0.10	0.08
3	1438	0.00	0.89	0.07	0.04
4	220	0.09	0.49	0.14	0.28
5	503	0.02	0.64	0.17	0.17

TABLE 2 Modeled Scenarios

	Filters				**Number of Observations**
	MC	Runway Configuration	Called Rates (ops/qtr-hr)	Fleet Mix (centroid) S, L, B757, H	
EWR	VMC	22L | 22R	18-24	0.01, 0.74, 0.14, 0.11	2043
	IMC	4R | 4L	16-20	0.01, 0.79, 0.12, 0.08	862
SAN	VMC	27 | 27	12	0.07, 0.85, 0.07, 0.01	7241
	IMC	27 | 27	12	0.06, 0.79, 0.09, 0.06	164

TABLE 3 Estimation Results

Airport	MC		Parameter				Capacity (ops/hr)*
			α	β	γ_1	γ_2	
EWR	VMC	Parameter	4.49	-0.34	-2.32	-2.61	**89**
		t-statistic	469.35	-22.66	-32.51	-34.12	
	IMC	Parameter	4.23	-0.16	-1.90	-1.85	**68**
		t-statistic	*289.16*	*-7.2*	*-13.65*	*-18.9*	
SAN	VMC	Parameter	3.87	-0.47	-2.12	-1.46	**48**
		t-statistic	*499.54*	*-43.28*	*-67.7*	*-53.73*	
	IMC	Parameter	3.57	-0.37	-2.07	-1.11	**35**
		t-statistic	*56*	*-3.63*	*-6.9*	*-6.39*	

* Capacity estimate with $\geq 95th$ percentile queue length, 50/50 arrival/departure split

TABLE 4 EWR Capacity Results with GDP Dummy, August-December 2006

MC	Configuration	Capacity (ops/hr)*	
		GDP	No GDP
VMC	22L|22R	**82**	**89**
IMC	22L|22R	**85**	**88**

* Capacity estimate with $\geq 95th$ percentile queue length, 50/50 arrival/departure split

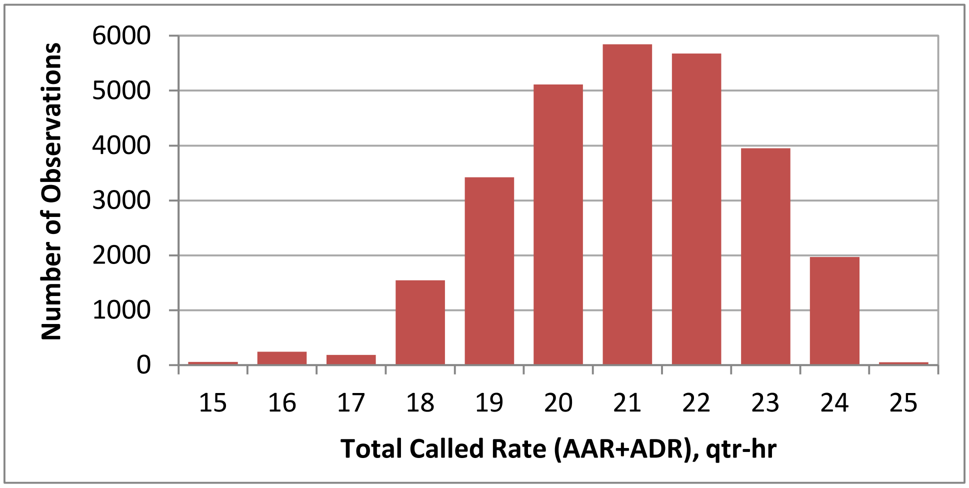

FIGURE1 Histogram of Total Called Rate per Quarter-Hour, EWR VMC 22L|22R

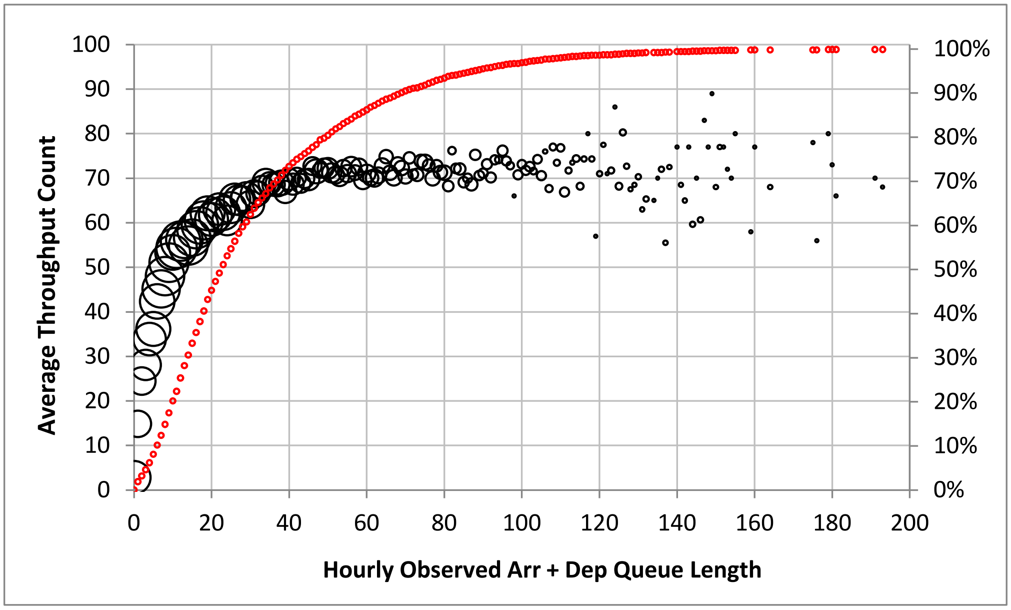

FIGURE 2 Total Count versus Queue Lengths, EWR VMC 22L | 22R

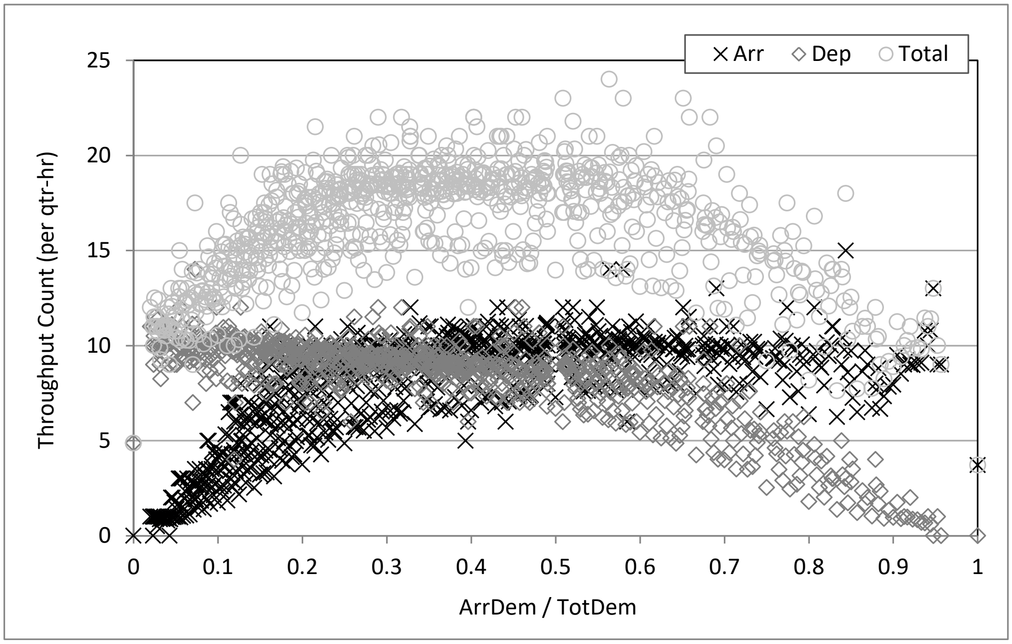

FIGURE 3 Aircraft Count (per Quarter-Hour) versus Arrival/Departure Split, EWR (All MCs)