

Estimating Airport System Delay Performance

Dr. Jerry D. Welch Richard T. Lloyd

MIT Lincoln Laboratory

Lexington, MA USA

welch@LL.MIT.EDU

rickl@LL.MIT.EDU

Abstract

It is generally agreed that delay in the national air transportation system will become intolerable if aviation capacity is not increased. But, before solutions can be implemented the aviation community must determine which airports most need additional capacity and how much they need. The FAA provides extensive data on traffic demand, flight delay, and airport capacity. But prioritizing solutions is difficult because of the complexity of the available capacity models and the interactions between terminal and en route capacity, both of which can be altered by weather and by flow control actions. Recent research has focused on determining “macroscopic” and “benchmark” capacities to make demand/capacity ratios reliable indicators of airport health and to help keep demand within practical capacity limits. In this paper we bound and refine those capacity estimates using steady state queuing to infer airport system capacity from valuable new FAA delay statistics. We compare overall airport system capacity with runway capacity to locate the origin of the major delays and to help identify airports most likely to benefit from improved runway capacity.

Introduction

To determine the impact of air traffic demand growth we need ways to relate demand to measures

of operational cost. The one operational cost measure for which statistics are readily available is air traffic delay. Convenient sources of FAA delay data are the Air Traffic Operations Network (OPSNET) [1] and the Consolidated Operations and Delay Analysis System (CODAS) [2]. OPSNET is a database of delay and operations statistics for major airports dating back to at least 1993 [1]. Its annual delay statistics count arrivals to each airport that were delayed by more than 15 minutes relative to their scheduled arrival times.

CODAS is a more detailed Internet-searchable database of delay and operations statistics for 100 major airports archived back to 1997. It provides taxi delays in addition to flight delays. Unlike OPSNET, which simply counts flights with large delays, CODAS reports the average delay per arrival for all flights. It reckons delays relative to planned flight duration as well as delays relative to scheduled gate arrival times. Its statistics are based primarily on direct reports from air carrier aircraft, and all of its estimates are derived automatically from objective data.

Many means are under consideration for increasing airport capacity or limiting demand. But to properly allocate resources we must determine which airports need capacity the most and how much. In addition to gathering, archiving, and disseminating data on traffic demand, flight delay, and airport capacity, we also need to relate delay (and delay growth) to capacity and demand and to estimate how much delay is independent of capacity and demand. This analysis can be hampered by the profusion of available delay and capacity metrics; they provide enough ranking

*This work was performed for the National Aeronautics and Space Administration under Air Force Contract No. F19628-00-C-0002. Opinions, interpretations, conclusions, and recommendations are those of the authors and are not necessarily endorsed by NASA.

options so that every major airport can be near the top of some priority list.

Recent research has focused on the estimation of a single capacity value for each airport. In this paper we review, compare, and refine these estimates. However, an airport system includes all the factors that govern the flow of aircraft towards each airport from all directions. We thus seek a way to estimate the performance of the entire system that governs the flow of aircraft to the airport.

The airport is the final server in the network of departure and en route sectors that limit the flow of arrivals. The effective capacity of the airport arrival system is less than the capacity of the airport itself because the airport is an element of the system and is connected in series with the system.

We show that steady state queuing theory can be used with the FAA's CODAS arrival count and airborne delay statistics to characterize the effective capacity of airport arrival systems, to bound and validate individual airport capacity estimates. Finally, we show that the ratio of arrival system capacity to airport capacity provides a quantitative means of identifying airport arrival systems most likely to benefit from improved runways capacity.

Published Capacity Estimates

We begin by reviewing published techniques for estimating average airport runway capacity. The first is the George Mason University Macroscopic Capacity Model (MCM) [8,9,10], which uses physical and operational characteristics of each airport to provide an upper bound on its runway capacity. The second is the Benchmark capacity, which the FAA obtains by combining estimates from experienced airport personnel with the standard FAA airport capacity model and with measurements of actual takeoff and landing rates.

George Mason University Macroscopic Capacity

Recent studies at George Mason University have developed a Macroscopic Capacity Model (MCM) to estimate peak airport runway capacity directly from the physical and operational characteristics of each airport that reduce its capacity relative to an upper limit based on its runway count. Its goal is to compare runway capacity simply and consistently over the entire population of airports.

The model considers a series of performance factors that determine the estimated maximum capacity of the airport in operations per hour.

These factors include the number of runways plus a Runway factor that accounts for reduction of runway efficiency from geometric interactions, and the number of gates plus a Gate factor that accounts for gate overloading.

Verification of MCM Peak Airport Capacity Estimates Using Arrival Rate Data

Peak airport capacity can be directly measured by examining short-term landing rates. Fifteen-minute landing rate counts available from CODAS provide a convenient way of estimating airport system performance. The CODAS database reports the number of aircraft that land in every 15-minute period. The occurrence distribution of these observed landing rates can be used to determine the achieved arrival statistics for an airport system.

Figure 1 shows the number of occurrences of arrival rates at DFW for all 15-minute periods from January to December 2000. (Periods with no arrivals are not shown. The absolute peak reported rate was 55 arrivals in 15 minutes, equivalent to 220 arrivals per hour. This rate was observed only once in the year, and it occurred in Visual Meteorological Conditions. The highest rate observed in Instrument Meteorological Conditions was 208 arrivals per hour, again only once in the year.

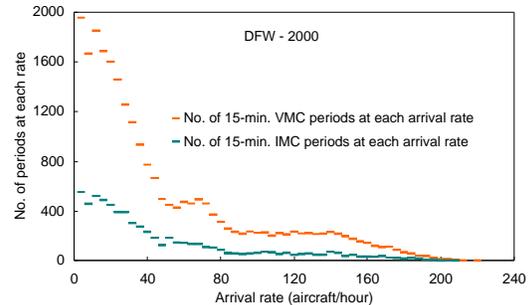


Figure 1. Distributions of arrival throughput occurrences in 15-minute periods at DFW in the year 2000 for VMC and IMC periods.

Analysis of the distribution in Figure 1 tells us that the 95th percentile arrival rate was 140/hr in both VMC and IMC. This verifies that the MCM estimate of 148 landings per hour is a reasonable estimate of DFW peak capacity. These peak rates are not sustained for long periods because DFW is a major hub for a single predominant carrier. Hence the peak rate estimate varies with the averaging time. We analyzed landing rate data for DFW using a 1-hour sliding window average for every 15-minute period in the month of February 2000 (the month for which the peak 15-minute rate was

220 arrivals per hour). Averaging over an hour caused the peak throughput to drop from 220/hr to 119/hr, and the 95th percentile capacity to drop from 140/hour to 96/hour.

FAA Benchmark Capacity

The FAA has developed a set of capacity benchmarks for 31 airports, where capacity is defined as the maximum number of flights the airport can routinely handle in an hour [11]. The benchmarks assume no constraints in en route airspace and provide separate rates for each airport based on good weather conditions and adverse weather conditions at the airport, as determined for the most common runway configuration.

The FAA estimated the benchmark rates from several sources. Peak rates provided by the air traffic facility at the airport and by the airport operator were compared to historical Aviation System Performance Metrics (ASPM) arrival and departure rate data. The FAA’s airfield capacity model [12] was also used to calculate rates, and a final consensus was developed by considering schedule data from the Official Airline Guide.

In addition to charts plotting all of the above information for arrivals and departures, the benchmark report summarizes the current capacity with four capacity values for each airport as illustrated in Table 1 for DFW. It also predicts future capacity from planned runway construction and from other planned improvements considered for implementation at the airport by the year 2010.

Table 1. Excerpt from the FAA Airport Capacity Benchmark report for (DFW)

| Scenario | Optimum Rate | Reduced Rate |
|------------------------|--------------|--------------|
| Today | 261-270 | 183-185 |
| New runway | 269-278 | 215-217 |
| + Planned improvements | 272-281 | 222-224 |

The report lists the planned improvements for each airport, but does not explain how the resulting capacity was estimated. The benchmark report does not estimate the percentage of time the airport typically operates at the reduced rate. However, it provides historical ASPM arrival and departure counts that it provides for actual traffic during one or two months of operation for each airport. These counts can be used to infer the fraction of time, K, the airport was in instrument meteorological conditions (IMC) and operating at the reduced rate.

To obtain an average arrival capacity for each airport we average, halve, and weight today’s benchmark operation rates for each airport:

$$\text{Ave. benchmark cap.} = \text{OR} \cdot (1-K)/2 + \text{RR} \cdot K/2$$

where OR is the average of the upper and lower “Optimum Rate” values and RR is the average of the two “Reduced Rate” values. When we assume that the IMC fraction K was 0.15 for DFW, the resulting average arrival benchmark capacity estimate for DFW is 126.6 aircraft/hour.

Steady State Queuing Capacity

When aircraft arrive at random and contend for service at the runway, queuing delay occurs on arrival even if demand is less than capacity. When traffic first begins to arrive in a system with excess capacity (demand/capacity ratio, ρ , less than 1), the queue length and the delay build exponentially with time. When demand is constant for a long period of time, the queue length eventually stabilizes at a steady state value. When steady demand approaches capacity, the time required to stabilize increases, and whenever ρ exceeds unity, the queue grows without limit.

Examples of Airport Queuing delay

Typical results of the transient queuing process are illustrated in Figures 2 and 3. Figure 2 is a plot of arrival rate and delay as a function of time at DFW on 10 April 2000 in visual meteorological conditions (VMC). The Arrival rate information was obtained from analysis of ARTS surveillance data [13]. The delay data was obtained from CODAS 15-minute airborne delay reports. Although the arrival rate only once exceeded the peak 95th percentile capacity of the airport, which is 140 arrivals per hour, delay built up significantly in the distinct arrival rushes.

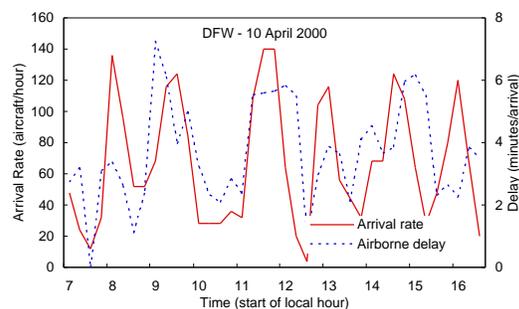


Figure 2. Arrival rate and airborne delay as a function of time at Dallas Fort Worth Airport (DFW) on 10 April 2000.

Between 7 AM to 4:30 PM, the delay varied from zero to 7.3 minutes per arrival, averaged 3.7 minutes per arrival, and accumulated to 44.6 aircraft-hours of delay.

Figure 3 is a plot of measured arrival rate and airborne delay as a function of time at LGA on 1

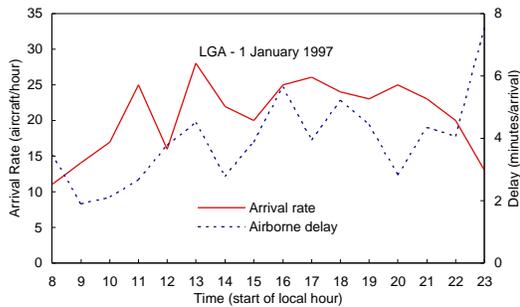


Figure 3. Arrival rate and airborne delay as a function of time at LaGuardia Airport (LGA) on 1 January 1997.

January 1997 in VMC. The arrival rate and the delay are plotted at 1-hour intervals. The Arrival rate and delay data are both from CODAS. The arrival rate never exceeded the capacity of the airport, which is about 40 arrivals per hour in VMC. Demand and delay are more uniform at LGA than at DFW. During the 15-hour period from 8 AM to 11 PM, the delay varied from 1.9 to 7.6 minutes per arrival, averaged 4.0 minutes per arrival, and accumulated to 21.9 aircraft hours of delay.

Properties of Steady State Queuing

One can use a steady state queuing model to calculate effective airport system capacity from annual averages of demand and airborne delay. Donohue and Laska [10] used CODAS “Total” delay for this purpose. However, CODAS Total delay is not defined in the CODAS documentation. A better metric for queuing delay is CODAS airborne delay, which compares actual flight times (wheels up to wheels down) with the flight time predicted by the aircraft operator in the amended flight plan at takeoff. Airborne delay does not include ground holds or taxi delays. It does not measure delay relative to the original airline schedule. It is reported for every 15-minute period in the day in units of minutes/arrival, and provides the best available measure of the effective queuing delay of the entire airspace system feeding the airport.

To compare delays quantitatively it is necessary to use the expression for total steady state queuing

delay for all arrivals at the airport over a given time period, typically a year. Total queuing delay is a function solely of demand/capacity ratio, and can be used for comparing numerical queuing delays among airports.

We use the queuing model for a single server queue with Poisson arrivals and exponential service times to calculate the expected value of the steady state delay per unit time [14]. When the demand/capacity ratio is less than 1, the expected queue length is

$$Q = \frac{\lambda^2}{\mu(\mu - \lambda)}$$

The accumulated queuing delay in a time period T is QT. Q and its derivative with respect to λ are plotted in Figure 4.

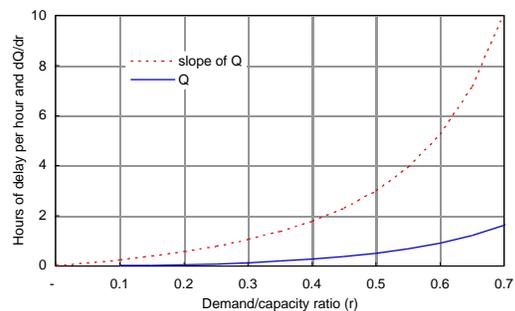


Figure 4. The steady state queuing curve and its first derivative.

Q increases quadratically with λ when λ is small. The slope first exceeds unity (steady state delay increases faster than demand) when demand exceeds 30% of capacity. When λ reaches 0.7, the slope of the curve exceeds 10, which means that a further 1% increase in demand increases steady state delay by 10%.

We use the queuing equation to infer each airport’s capacity from its arrival count and total CODAS airborne delay. A convenient time period for this calculation is a calendar year. The CODAS database provides annual summaries of total arrival counts and total Airborne delay for 100 airports. We divide the total annual airborne delay (in minutes) by the number of minutes in a year to get the value of Q for each airport for that year. We then solve for λ as a function of Q, and divide the average hourly arrival rate by λ to get the effective queuing capacity. Following the procedure used by Donohue and Laska we use an effective year of 350 days, each with 16 hours of flight operations.

A steady state queuing model does not accurately represent transient queuing activity. When we

apply the steady state queuing equation to calculate the capacity that corresponds to the *average* demand and delay during the period plotted in Figure 2, the resulting capacity average capacity for DFW is 79 arrivals per hour, which is significantly less than its actual VMC capacity. The steady state queuing capacity computed from the average demand and delay at LGA during the period plotted in Figure 3 is 30 arrivals per hour, about three-fourths of LaGuardia’s peak VMC capacity of 40 arrivals per hour. Steady-state queuing theory estimates capacity better at airports that experience steady demand.

Using Steady State Queuing to Bound Capacity Estimates

Steady state queuing can be used to validate other capacity estimates by providing a lower bound on average capacity. Because of the nonlinear increase in queuing delay with traffic intensity, actual queuing delay for a system with variable demand is always larger than the delay calculated from the demand average. Thus, if a capacity estimate for an airport cannot be lower than the queuing capacity inferred for that airport from average delay and demand statistics.

CODAS data is subject to errors that could decrease apparent delay and thereby increase the inferred queuing delay. Airborne delays are computed relative to operator estimates of flight time at takeoff. There is no standard basis for operator flight time estimates. Because these estimates cannot predict times less than the absolute minimum possible flight duration they are almost surely biased in the positive direction. When a flight time estimate is biased positively, the resulting delay appears smaller, and the inferred queuing capacity will be over-estimated.

Furthermore, CODAS obtains its delay and demand data principally from automatically reported data. Some air carrier and most commuter and cargo aircraft do not provide automatic reports. For statistical purposes, CODAS must estimate the airborne delay for unequipped aircraft by using ETMS data and published airline schedules as well as whatever other sources of delay and flight data may be available. Resultant errors could bias the inferred capacity in either direction.

Comparing Capacity Estimates

We used CODAS data with the queuing model to estimate the effective queuing capacity for all of the airports in the CODAS database. The resulting

capacity estimates for 26 airports are included in Figure 5 along with the MCM and average benchmark capacity estimates for the same airports. In deriving the benchmark capacities we assumed that the IMC fraction K was 0.15 for all airports except Phoenix (PHX), for which we set K to 0.01.

The MCM capacity, being an estimate of the peak runway capacity, would normally be expected to exceed the average benchmark capacity. However, MCM capacities for 10 of the airports are less than the average benchmark estimates. Furthermore, the MCM runway capacity estimates for PHL, LGA, MSP, SEA, and SFO in Figure 5 are all less than or equal to the queuing estimates for the same airports, indicating a serious under-estimation of their peak capacities by the MCM parameters.

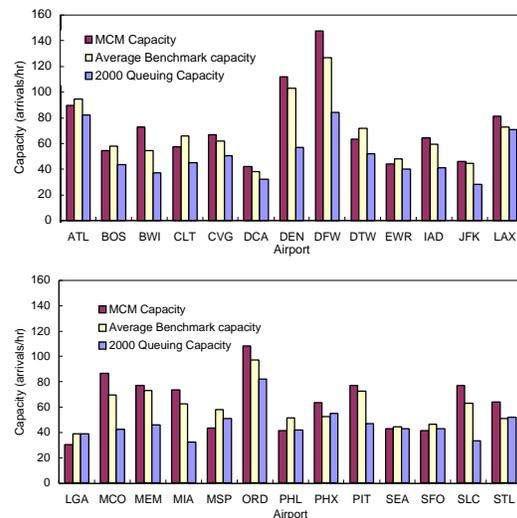


Figure 5. George Mason University MCM Runway Capacity, Average Benchmark Capacity, and Effective Queuing Capacity for 26 US Airports.

We conclude that a better estimate of peak arrival capacity can be obtained from the maximum of the two “optimum” benchmark rates.

The relationship between the average benchmark estimate and the queuing bound appear reasonable for all but six airports: ATL, LAX, LGA, SEA, STL, and PHX. The average benchmark estimates for ATL and LAX are only slightly larger than the queuing limit. This may reflect the fact that, unlike DFW, these two major airports operate with continuously high demand. The average benchmark estimates for LGA and SEA airports are very close to the queuing limit. The average benchmark capacity for STL is slightly less than the queuing limit, and the average benchmark capacity

for PHX is considerably smaller. We re-examined the benchmark estimates for these airports and found that the data in the benchmark report warranted an adjustment to the average capacity estimates for PHX, STL, LGA, and SEA. The next section explains the need for each adjustment and the gives the resulting adjusted capacity.

Adjusted Average Benchmark Capacities

The benchmark estimate for Phoenix showed the largest discrepancy and proved both the sensitivity of the CODAS airborne delay metric and the value of the queuing bound. We found that the benchmark study had acknowledged, but not taken into account, the opening of the new runway at PHX in the fall of 2000. The availability of the new runway for the last three months of 2000 was reflected in the average CODAS airborne delay for the year. According to the benchmark report the new runway was expected to increase the capacity of PHX to 70.5 arrivals per hour. It became operational on 5 October, and thus raised the weighted mean annual capacity of PHX in 2000 to more than 57 arrivals per hour. This comfortably exceeds the queuing capacity bound of 55.3 arrivals calculated from CODAS delay data for PHX.

The summary capacity table for STL in the benchmark report indicates that today’s capacity at STL drops from an “Optimum Rate” of 104-112 to a “Reduced Rate” of 64-65. However, the April 2000 ASPM data for STL instrument approaches shows that the actual capacity of the airport in instrument conditions was greater than the reduced rate of (32,32) reported by the facility and calculated by the FAA Capacity model. The distribution of observed arrival and departure rates in IMC hours was nearly identical to the distribution in VMC hours in April 2000, implying that the reduced rate should equal the optimum rate. When this adjustment is made, the average benchmark capacity for STL increases from 51 to 54 arrivals/hour, which is larger than the queuing bound of 52 arrivals per hour as determined from CODAS airborne delay at STL in 2000.

The benchmark report indicates that capacity at LGA drops from an optimum rate of 80-81 to a reduced rate of 62-64. However, the April and October 2000 ASPM data for LGA tell a different story. The actual capacity of the airport in visual conditions appears to be 90 operations per hour, rather than 80. The distribution of observed arrival and departure rates in IMC hours implies that the reduced rate is also larger than reported in the summary table. It appears to be 80 operations per

hour rather than 64. When these adjustments are made, the average benchmark capacity for LGA increases from 39 to 44 arrivals/hour, which is larger than the queuing bound of 39 arrivals per hour.

The summary capacity table for SEA in the benchmark report indicates that capacity at SEA has an optimum rate of 90-91. This optimum rate is consistent with the supporting data in the report, but the April and July 2000 ASPM data for SEA indicate that the actual arrival capacity of the airport in instrument conditions appears to be about 42 arrivals per hour rather than 40 as implied by the reduced rate of 78-81 operations per hour. When this adjustment is made, the average benchmark capacity for SEA increases from 44 to 45 arrivals/hour, which is larger than the SEA queuing bound of 43.

The adjusted benchmark capacity estimates for these four airports are summarized in Table 2. The adjusted capacity for Phoenix applies only after 5 October 2000, when the new runway became operational.

Table 2. Adjusted benchmark capacity estimates for Four Airports, whose published benchmark capacities were inconsistent with the queuing bound.

| Airport | Optm Rate (ops/hr) | Rdcd Rate (Ops/hr) | K | Ave. (Arr/hr) |
|---------|--------------------|--------------------|-----|---------------|
| PHX | 137-146 | 96-101 | .01 | 71 |
| STL | 104-112 | 104-112 | .15 | 54 |
| LGA | 90-90 | 80-80 | .15 | 44 |
| SEA | 90-91 | 84-84 | .15 | 45 |

Figure 6 plots CODAS Airborne delay as a function of demand/capacity ratio for each of the 26 airports of Figure 5. The demand/capacity ratio for each of the airports is calculated using the average benchmark capacity (adjusted for 4 of the airports) divided by the reported CODAS demand for the airport in the year 2000. The chart compares the delay reported at each of the airports with the total annual queuing delay predicted by the queuing model. The benchmark adjustments achieved the desired goal: the airborne delay for each airport is larger than the queuing delay that would be generated at an airport with a constant adjusted benchmark capacity and constant demand. The demand/capacity ratios for most of these airports exceed 0.5, indicating that further increases in

demand will result in disproportionate increases in queuing delay.

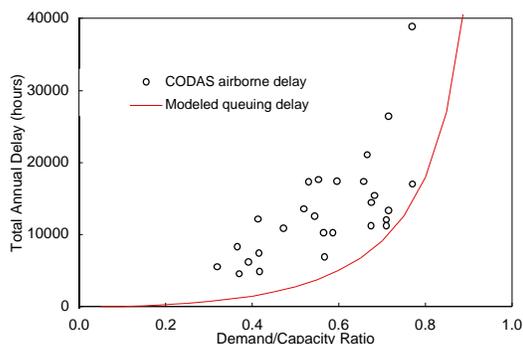


Figure 6. Total annual CODAS airborne delay reported at 26 airports compared with the delay curve predicted by the queuing model using average benchmark capacity (with adjustments).

Table 3 summarizes the average benchmark arrival capacities for 26 airports with adjustments. It includes queuing capacity as a measure of the effective capacity of the airport arrival system. It also includes demand/capacity for each airport.

The lowest ratios of arrival system capacity to benchmark capacity generally occur at airports that also have low average demand relative to capacity. MIA, SLC, DEN, MCO, JFK, and MEM have the lowest system/runway capacity ratios, implying that most of the airborne delay for arrivals to these airports occurs in en route airspace. These airports would benefit from en route improvements, but they do not appear to be the best candidates for new runways or other runway capacity improvements among the major airports listed.

Some busy single-carrier hubs like PIT, DFW, and DTW also have low system/runway capacity ratios, implying that much of their airborne delay occurs in en route airspace. These airports would be expected to benefit from more runway capacity because they experience large demand variations and large peak delays from transient queuing. However, additional runway capacity could be exploited more effectively during rushes if it were matched by an improvement in en route capacity.

System capacity and runway capacity are most closely matched at high traffic intensity airports like LAX, SEA, SFO, STL, and LGA. These runway-limited airports do not appear to be significantly impacted by en route capacity problems. They have relatively steady traffic and, with the possible exception of STL, do not experience significant hubbing. These airports would seem to be the best candidates for new runways and other capacity enhancements. However, flow control procedures can translate airborne delay to arrival delay and make any airport system appear to have more en route capacity than it actually has. Ground holding meters flights so that they experience less flight delay, thereby shifting delay from flight to ground. Reduced airborne delay makes system capacity as calculated from queuing appear larger than actual. But reducing airborne delay by ground holding does not change the fact that aircraft still land behind schedule. It is necessary to also examine delay relative to schedule (CODAS Arrival delay) to determine with certainty how much an airport is likely to benefit from improvements to runway capacity alone. The next section explores examples of delay shifts from flight delay to schedule delay.

Table 3. Average Capacity Estimates (arrivals/hr) and Average Demand/Capacity Ratio (ρ) in the year 2000 for 26 Airports.

| | ATL | BOS | BWI | CLT | CVG | DCA | DEN | DFW | DTW | EWR | IAD | JFK | LAX |
|----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Ave. Benchmark Cap. | 95 | 58 | 55 | 66 | 62 | 38 | 103 | 127 | 72 | 48 | 60 | 45 | 73 |
| Queuing Capacity | 82 | 43 | 37 | 45 | 50 | 32 | 57 | 85 | 52 | 40 | 41 | 28 | 71 |
| ρ in 2000 | .77 | .60 | .42 | .52 | .59 | .57 | .41 | .53 | .54 | .66 | .55 | .42 | .77 |

| | LGA | MCO | MEM | MIA | MSP | ORD | PHL | PHX | PIT | SEA | SFO | SLC | STL |
|----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Ave. Benchmark Cap. | 44 | 70 | 73 | 62 | 58 | 97 | 52 | 71 | 73 | 45 | 46 | 63 | 54 |
| Queuing Capacity | 39 | 42 | 46 | 32 | 51 | 82 | 42 | 55 | 47 | 43 | 43 | 34 | 52 |
| ρ in 2000 | .68 | .39 | .37 | .32 | .68 | .72 | .67 | .71 | .47 | .71 | .67 | .37 | .72 |

Relating rate and delay

We examined delay shifts at DFW and EWR, two important but distinctly different types of airports. DFW is a large hub with large capacity and experiences low airborne delay. EWR is smaller, has less runway capacity, has a higher average demand/capacity ratio with more continuous demand, and always ranks first or second nationally in airborne delay.

Figure 7 graphs the average CODAS Airborne delay at DFW for each value of 15-minute throughput observed in the year 2000. We divided the year into VMC and IMC intervals. As would be expected, for a given throughput observation, the expected value of delay is larger when instrument conditions prevail in the observation period. However, the airborne delay for all aircraft that landed in a short period with a given rate does not increase rapidly with arrival rate as would be expected for a fixed capacity queue.

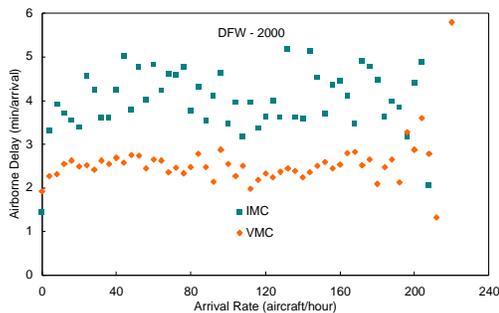


Figure 7. CODAS Airborne delay averages at DFW for each 15-minute value of throughput for VMC and IMC periods in the year 2000.

There are several reasons for this result. The average delay for the arrivals in a short period is always influenced by upstream events preceding the period. The worst delays occur in hazardous weather, often far from the runway both in space and time. Flow management deliberately holds arriving aircraft upstream where they can be safely accommodated rather than letting queues grow in congested terminal airspace where the actual bottleneck may exist.

Queuing behavior is also not seen in this figure because the independent variable in these plots is the observed throughput (which is less than demand when capacity is exceeded), and the system capacity is not constant. The plotted delay values are averages for all the 15-minute periods that experienced the same throughput. The data includes arrivals to DFW from all airports. When

we examine all of the 15-minute intervals that have the same arrival rate, we find that the effective capacity of this complex arrival network can vary from zero to the observed peak of 220 arrivals/hr. Each plotted delay value is an average of many individual period averages. The individual periods that belong to each throughput bin themselves experience many different conditions ranging from steady demand with excess system capacity to transient demand with a capacity deficit.

These results confirm that the effective capacity for an airport arrival system is lower than the runway capacity of the airport. Airborne delay at low arrival rates would be small if queuing by itself at a fixed-capacity airport caused the airborne delay. Then delay would increase with demand according to the queuing curve. The near invariance of delay to throughput indicates that most of the flight delay that occurs when the throughput is low is caused by slowdowns in other parts of the system.

Flight delays at low throughput are most often caused by inadequate capacity in the en route sectors feeding the airport and by reduced capacity from hazardous weather. Both of these en route capacity deficits are made worse if flow control procedures further restrict en route capacity or cause reduced system capacity before and after the flow is blocked by hazardous weather. When reduced system capacity is forecast, the flow control system often intervenes to limit airborne delay by delaying departures. When the system capacity is high, there is no need for departure holding. The invariance of delay to throughput reflects the action of flow control procedures in maintaining constant delay.

CODAS Arrival delay, which measures delay relative to schedule, is the sum of the airborne delay and any delay relative to schedule that was experienced before takeoff or after landing. It therefore reflects the influence of traffic flow management actions.

Figure 8 graphs the CODAS airborne and arrival delay averages at DFW for each 15-minute throughput value observed during IMC periods in the year 2000. Airborne delay is almost independent of throughput, but arrival delay decreases as throughput increases. When throughput is low, delay relative to schedule is large. When throughput is high and there is no need for ground holds, the arrival delay average is nearly equal to the airborne delay average. These results confirm the conclusion obtained from the ratio of system capacity to network capacity that DFW is capacity limited by en route airspace.

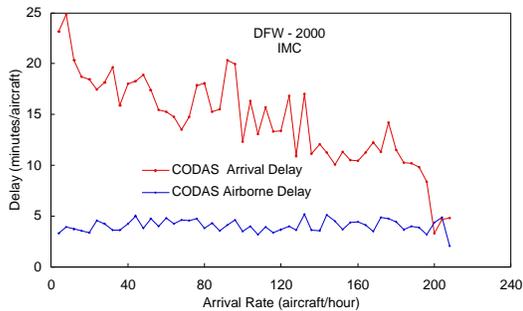


Figure 8. CODAS Airborne and Arrival delay averages at DFW for each 15-minute throughput value observed during IMC periods in 2000.

Figure 9 graphs the CODAS airborne and arrival delay averages at EWR for each 15-minute throughput value observed during VMC periods in the year 2000. At all but the highest throughput rates the arrival delay remains high at Newark, even in VMC. The arrival delay and airborne delay finally converged (i.e., there was no departure delay) in the three 15-minute periods in the year 2000 for which a throughput of 72 arrivals per hour was achieved. Airborne delay increased slightly with throughput. This indicates that some runway queuing takes place at the Newark airport. Yet, like at DFW, most of the EWR delay occurs upstream.

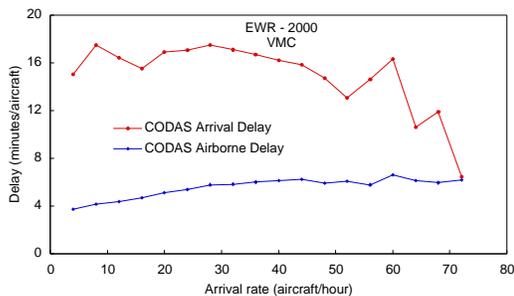


Figure 9. CODAS Airborne and Arrival delay averages at EWR for each 15-minute throughput value observed during VMC periods in 2000.

The traffic flow management process effectively constrains flow to prevent excessive queuing at the airport. A major goal of traffic flow management is to prevent queue build-up at any location in the system that is predicted to experience a capacity deficit. Since the control feedback loop is closed around all airspace (including terminal airspace where serious capacity bottlenecks regularly occur) airport and terminal airport capacity are integral parts of the system dynamics, even if excessive queuing is seldom observed there. This ability to shift the location of the delay can obscure the need

for system capacity improvements. In spite of the delay shifting that occurs in en route airspace at Newark, its airborne delay, and therefore the ratio of its system capacity to its runway capacity are relatively large (0.83). This places Newark among the airports that could clearly benefit from runway capacity improvements, and validates the value of airborne delay as a ranking indicator for capacity benefits.

Conclusions

Capacity estimates for U.S. airports convey a sobering message. Most major airports operate at traffic intensities such that airborne delay is growing several times faster than demand. If the capacity of these airport systems (including the en route airspace that serves them) is not also increased significantly, these airports will not be able to support further demand growth without experiencing unacceptable operational cost.

FAA CODAS delay data is useful in assessing the delay performance of individual airports. Performance estimates based on direct measurement of airport throughput and delay are particularly informative because queuing models can be used to relate throughput and delay to effective system arrival capacity.

The capacity needs of an airport can be assessed by comparing the ratio of the effective capacity of the entire airport arrival system to the runway capacity of the airport itself. The best estimate of runway capacity is presented in the FAA benchmark report. Queuing theory can be used to infer airport arrival system capacity from appropriate FAA demand and delay statistics. The queuing model also provides a lower bound on estimates of runway capacity.

Low ratios of system to runway capacity occur at MIA, SLC, DEN, MCO, and JFK. This implies that most of the airborne delay at these airports occurs in en route airspace. These airports would benefit from en route improvements, but they do not appear to be the best candidates for new runways or other runway capacity improvements.

The capacity ratio is large for LAX, SEA, SFO, STL, and LGA. These airports have high traffic intensity but do not appear to be as strongly affected by en route capacity problems as other major airports. Such airports would seem to be the best candidates for new runways or other runway capacity enhancements.

However, flow control procedures can translate airborne delay to arrival delay and make an airport

system capacity metric that is based on airborne delay appear to have more en route capacity than it actual does. Reducing airborne delay by ground holding does not change the fact that aircraft still land behind schedule. It is thus necessary to also examine delay relative to schedule to determine how much such an airport is likely to benefit from improvements to runway capacity.

References

- [1] Federal Aviation Administration Office of Policy and Plans, "Airport Capacity Benchmark Report 2001," www.faa.gov/events/benchmark (September 2001)
- [2] Federal Aviation Administration Office of Policy and Plans, "Consolidated Operations and Delay Analysis System," www.apo.data.faa.gov. (April 2001)
- [3] Weidner, T., "Capacity Related Benefits of Proposed CNS/ATM Technologies," 2nd USA/EUROPE Air Traffic Management R&D Seminar, Orlando, FLA, (December 1998).
- [4] Lee et al, "Estimating the Effects of Terminal Area Productivity Program," NASA Contractor Report CR-1997-201682 (April 1997).
- [5] Boswell, S.B. and Evans, J.E., "Analysis of Downstream Impacts of Air Traffic Delay," Massachusetts Institute of Technology, Lincoln Laboratory Project Report ATC-257, (March 1997)
- [6] Beatty, R. et al, "Preliminary Evaluation of Flight Delay Propagation Through an Airline Schedule," 2nd USA/EUROPE Air Traffic Management R&D Seminar, Orlando FLA (December 1998).
- [7] Welch, J.D., Andrews, J.W., and Robinson, J. E., "Assessing Delay Benefits of the Final Approach Spacing Tool (FAST)," AIAA Guidance, Navigation & Control Conference, Montreal, (Aug 2001).
- [8] Donohue, G.L., "A Simplified Air Transportation System Capacity Model," J. Air Traffic Control, (April-June 1999).
- [9] Donohue, G.L., "A Macroscopic Air Transportation System Capacity Model," Symposium on ATM in 21st Century, Capri Italy, (Sept 1999).
- [10] Donohue, G.L. and Laska, W.D., "United States and European Airport Capacity Assessment using the GMU Macroscopic Capacity Model (MCM)," 3rd USA/EUROPE Air Traffic Management R&D Seminar, Napoli, (June 2000).
- [11] Federal Aviation Administration Air Traffic Tactical Operations Program Office (ATT-200, "Air Traffic Operations Network (OPSNET)," www.apo.data.faa.gov/opsnet (September 2001)
- [12] "Upgraded FAA Airfield Capacity Model (User's Guide)," FAA-DF-81-001A, May 1981
- [13] Andrews, J. W. and Robinson, J.E., "Radar-Based Analysis of the Efficiency of Runway Use," AIAA Guidance, Navigation & Control Conference, Montreal, (Aug 2001).
- [14] Wohl, M. and Martin B.V., "Traffic System Analysis for Engineers and Planners," McGraw-Hill, New York, 1967.

Author Biographies

Jerry D. Welch, MIT Lincoln Laboratory

Dr. Welch is a Senior Staff Member of the Air Traffic Control Systems Group MIT Lincoln Laboratory, and was formerly leader of the Air Traffic Automation Group. He has been responsible for assisting the FAA and NASA in the development of computer aides for air traffic controllers. He was part of the team that developed the FAA's Mode S air traffic control radar beacon system. He led Lincoln Laboratory's program to develop surveillance techniques for the Traffic Alert and Collision Avoidance System (TCAS). He helped initiate the FAA's Terminal Air Traffic Control Automation Program at which led to NASA's Center TRACON Automation System (CTAS) activity. He led efforts to develop and test automation to alert pilots to hazards on the airport surface. This resulted in a successful live demonstration of automatic Runway Status Lights driven by a surface surveillance radar at Boston. He led Lincoln Laboratory efforts to help the FAA define new oceanic and en route automation infrastructure and new flight data processing and surveillance data processing software. He examined the use of surface surveillance to improve surface traffic management and to help reduce taxi delay. He is currently studying the quantitative delay benefits of CTAS, investigating measures of airport capacity, and analyzing sources of aviation delay.

Richard T. Lloyd, MIT Lincoln Laboratory

Mr. Lloyd is a Technical Staff Member of the Air Traffic Control Systems Group at MIT Lincoln Laboratory. His work over the past ten years has been focused on the Center/TRACON Automation System (CTAS), the Enhanced Traffic Management System (ETMS) and the Integrated Terminal Weather System (ITWS). He designed and developed a method for managing a distributed software/hardware system which became the model for the Monitor and Control System that is part of the FAA's Free Flight Phase 1 implementation of CTAS. His work on the integration of CTAS, ETMS and ITWS has enabled data sharing between the three automation systems.