An Airspace Concept Evaluation System Characterization Of National Airspace System Delay

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This paper presents an analysis of National Airspace System (NAS) delay. An interacting set of models called the Airspace Concept Evaluation System (ACES) was used to simulate one day of NAS-wide air traffic. A total of 36 simulations were run. They included nine different airport capacity conditions across the NAS and four levels of NAS-wide demand. The analysis of delay results for these 36 simulations shows that delay increases quadratically with increased demand. The delay versus capacity curves have linear trends. However, nonlinearities within these curves expand with increased demand. These nonlinearities suggest that additional factors such as regional concentrations of airports in low capacity conditions due to regional weather do have a significant influence on the results. This analysis is an important first step in exploring and understanding the intricacies of the NAS so that further efforts can be made to improve it.

I.   Introduction

Over the past several decades, the demand for air travel has increased. The National Airspace System (NAS) has evolved with modest advances in weather/wind prediction, faster and quieter airplanes, and by adding new runways and technologies at airports. Each small step plays a part in the attempt to minimize delay as demand continues to grow. However, current technology is fast approaching the point of diminishing returns. New airspace operational concepts will be necessary to reverse this imbalance. These conceptual changes may affect the entire NAS in unpredictable ways.

The Airspace Concept Evaluation System (ACES) is a NAS-wide fast-time simulation developed at NASA Ames Research Center. ACES simulates a model of the NAS with interacting agents for center control, terminal flow management, airports, individual flights, and other NAS elements. These agents pass messages between one another similar to real world communications. This distributed agent based system is designed to emulate the highly unpredictable nature of the NAS, making it a suitable tool to evaluate envisioned airspace concepts. Before new concepts can be evaluated, the tool must be used to evaluate the current NAS situation. This will lead to the development of processes that attempt to better understand the interdependencies between elements making up the NAS. Through these processes, the cascading effects that interdependencies produce on the system can be better understood.

As a first step, this study was performed to establish an initial characterization of NAS-wide delay. The goal was to use ACES to simulate a variety of demand and capacity scenarios in the NAS to quantitatively establish their effects on system-wide delay.

The study included thirty-six simulations, each encompassing a 24-hour demand period. The simulations varied in flight demand and airport operational capacity.

Four flight demand cases were studied which included a representation of current-day 2002, an approximate doubling of current-day 2002, and two intermediate flight demand schedules. All cases included domestic commercial passenger flights operating between the top 98 US airports.

Capacity was varied with nine cases representing different airport operational capacities. Two cases represented optimum and worst-case airport states. All airports operated under visual flight rules (VFR) during the simulation period for the optimum case. For the worst case, the 30 benchmark airports[8] operated

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under instrument flight rules (IFR) during the simulation period. The remaining seven intermediate days represented airport operational conditions from historic weather days.

Delays for each segment of flight were determined and mapped against demand and capacity. The resulting surface provides a quantification of the effect that demand and capacity have on NAS delay.

II.   ACES Environment

ACES simulates the NAS using individual models for each of the communicating agents within the system. Examples of agents include System Command Center, Air Route Traffic Control Center (ARTCC), and Terminal Radar Approach Control (TRACON). ACES is different from other NAS simulation tools in that it can simulate and record all communications between agents for post analysis.

ACES Build 1.2 is the first working version of ACES. This build emphasizes the assembly of an agent-based framework with lower emphasis on developing high-fidelity agent models. Models or functionality which are absent in this current version of ACES include: 1) sector capacity limits, 2) separation constraints, 3) flight plan rerouting, 4) delay in the arrival terminal area and arrival surface, and 5) en-route altitude and cruise speed changes. Additional and enhanced models and improved functionality in these areas are under current development.

Two options that are available in ACES Build 1.2 are delay maneuvers and TRACON departure fix separation. Delay maneuvers are lateral en route course alterations used to delay individual flights. The TRACON departure fix separation option provides a simulation of miles-in-trail separation of aircraft at each departure fix.

III.   Demand Variation

Demand is defined as the number of flights flown in the simulation. It is primarily dependant on the flight data set, which is a list of scheduled flight plans for the simulation. Each flight plan includes departure and arrival airports, cruise altitude and speed, a planned trajectory specified as an array of latitude/longitude coordinates, and scheduled departure time. Each flight is individually flown unconstrained between origin and destination airports during ACES configuration. This establishes the scheduled take-off, landing and gate arrival times.

Although no flights are cancelled, not all flight plans are loaded and flown in the simulation. ACES rejects and filters out flights during configuration. Reasons why ACES rejects flights include: 1) when the origin and destination airports are the same, 2) sector boundary definition errors resulting in flights passing through undefined airspace, 3) inadequate number of way points in planned trajectories, and 4) distance between consecutive way points exceeds a pre-defined value.

Two flight data sets were readily available for this characterization study. The first was a current-day-demand constructed from recorded traffic for May 17, 2002.[1] The second data approximately doubled the current-day traffic. This data set was developed as a future demand representing a nominal day in the year 2020.[2] The two data sets included domestic commercial passenger flights between pairs of airports within the continental United States' top ninety-eight airports. At run-time, ACES loaded 16,468 flights for the current-day demand set, and 33,186 flights for the future demand set.

Intermediate flight data sets were created by filtering flights from the future data set while maintaining similar flight distributions. Let $\mathbf{T}(A, Q)$ and $\mathbf{L}(A, Q)$ be matrices containing the number of flights scheduled to takeoff and land at airport A at quarter hour Q from the start of the simulation. Let α be the reduction ratio desired. Then $\mathbf{T}_r(A, Q) = \alpha \mathbf{T}(A, Q)$ and $\mathbf{L}_r(A, Q) = \alpha \mathbf{L}(A, Q)$ become the matrices of the number of flights that must be removed per airport per quarter hour to reduce the data set by α. For each flight, let A_t and A_l be the takeoff and arrival airport. Let Q_t and Q_l be the scheduled takeoff and landing quarter hours from the start of the simulation. The flight filtering algorithm is as follows.

For each loaded flight in the future demand data set:
If $(T_r(A_t, Q_t) > 0.5)$ and $(L_r(A_l, Q_l) > 0.5)$:
Remove flight and decrement $T_r(A_t, Q_t)$ and $L_r(A_l, Q_l)$ by 1
Else:
Add flight to new data set.

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Two intermediate data sets were reduced from the future demand data set with $\alpha = \frac{1}{6}$ and $\alpha = \frac{1}{3}$. At run-time ACES loaded 25,597 and 20,461 flights respectively from these intermediate data sets. These data sets combined with the current demand and future demand provided 4 equally distributed variations of demand with similar flight distributions.
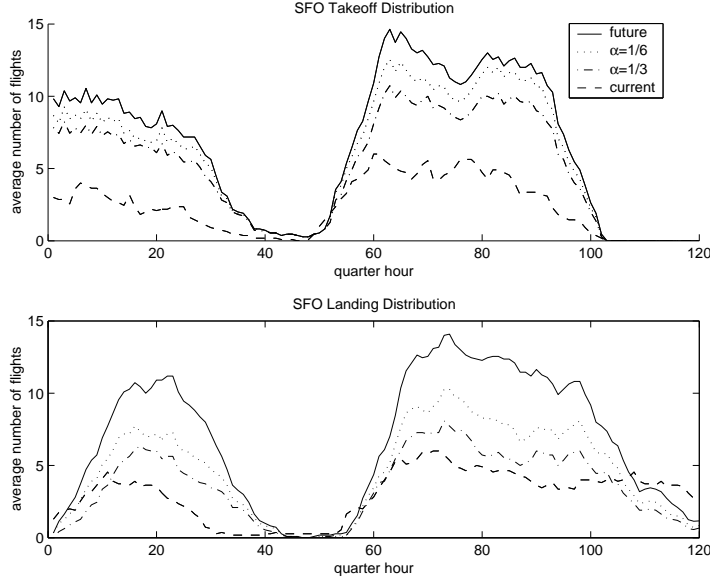

Figure 1. Takeoff and landing flight distributions at SFO for each demand data set.

Figure 1 shows the flight distributions for San Francisco International Airport (SFO) as a running average of scheduled takeoffs and landings per quarter hour starting at midnight Greenwich Mean Time (GMT). It is apparent from the figure that the defined filtering algorithm produced two intermediate demand data sets with similar distributions to that of the future demand set. These three distributions also compare favorably with the current-day demand distribution.

IV.   Capacity Variation

Capacity has been defined in many ways. En-route capacity has been defined as a function of the total number of aircraft under track control in a sector, average time of a flight in a sector, and ratio of total altitude changes to number of aircraft.[6] Airport capacity has been defined as airport operations (arrivals, departures, or total) divided by throughput[7] or most commonly, as airport operations per unit time.[4, 5] In all cases, capacity is defined for a single sector or airport. For the purpose of this analysis, a single capacity value encompassing the entire NAS is needed. This single capacity value must be independent of any one airport or region and independent of total demand or delay. The most appropriate NAS-wide capacity calulation that could be made using ACES Build 1.2 is a combined maximum airport capacity defined in terms of operations per quarter hour.

ACES models each airport's state per quarter hour of run-time as either Visual Flight Rules (VFR) or Instrument Flight Rules (IFR). This operating state in turn defines the airport's capacity as the maximum number of departures, arrivals and total operations. A simple average of all airport capacities throughout the day would neglect the fact that demand is placed more heavily on some airports than others. Therefore, NAS capacity was calculated as a weighted average of airport capacities throughout the day across the scheduled demand distribution, and normalized by total demand D. The resulting NAS capacity is dependant on the demand distribution and not the total demand itself. NAS capacity units remain the number of operations per quarter hour just as with individual airport capacities. Let the matrices $\mathbf{C}_d(A, Q)$, $\mathbf{C}_a(A, Q)$, and $\mathbf{C}_t(A, Q)$ contain the maximum airport capacities for departures, arrivals, and total operations for airport A at quarter hour Q from the start of the simulation. The respective NAS capacity measurements are given

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as

$$C_{NASa} \quad = \quad \frac{1}{D}\sum \mathbf{L}(A,Q) \cdot \mathbf{C}_a(A,Q)^{\intercal} \tag{1}$$

$$C_{NASd} \quad = \quad \frac{1}{D}\sum \mathbf{T}(A,Q) \cdot \mathbf{C}_d(A,Q)^{\intercal} \tag{2}$$

$$C_{NASt} \quad = \quad \frac{1}{2D}\sum \left(\mathbf{L}(A,Q) + \mathbf{T}(A,Q)\right) \cdot \mathbf{C}_t(A,Q)^{\intercal} \tag{3}$$

where $\mathbf{T}(A,Q)$ and $\mathbf{L}(A,Q)$ are the takeoff and landing distribution matrices defined in section III.

The variation of each airport's state throughout the day can be used to emulate the effects of terminal area weather. These variations affect airport capacity and therefore NAS capacity. Higher NAS capacity values result when the majority of airports are operating in VFR conditions during most of the day. Lower NAS capacity values result when IFR conditions occur more often. The greatest NAS capacity for a given demand results when all airports are in VFR conditions all day. A worst case low capacity day was defined as a day when the top 30 continental airports are in IFR conditions all day. Intermediate NAS capacities were calculated using airport state conditions taken from Aircraft System Performance Metrics (ASPM) analysis weather reports for various historical days. A report by Metron Aviation provided convenient access to this data for 7 different days.[3] Three of these days were reported as low weather days. The remaining four were reported as days where weather affected delay. Since the simulations are based on the top 98 continental airports, and ASPM reports provide airport state data for only the top 49, the remaining airports were always assumed to be in a VFR state.

V. Delay Calculations

ACES can collect all messages between its various agents, but only aircraft state messages were necessary for this analysis. The aircraft state message for each flight includes the origin and destination airports, and the scheduled and actual simulation times for gate departure, takeoff, landing, and gate arrival. For each flight, let t_d, t_t, t_l, and t_a define the actual gate departure, takeoff, landing, and gate arrival times. Similarly, let t_{ds}, t_{ts}, t_{ls}, and t_{as} define the scheduled times. Delay can be attributed to departure delay d_d, takeoff surface delay d_t, enroute delay d_l, or landing surface delay d_a. The sum of these is total delay d_{total}. The following are the calculations for each delay element.

$$d_d \quad = \quad t_d - t_{ds} \tag{4}$$

$$d_t \quad = \quad (t_t - t_{ts}) - d_d \tag{5}$$

$$d_l \quad = \quad (t_l - t_{ls}) - d_d - d_t \tag{6}$$

$$d_a \quad = \quad (t_a - t_{as}) - d_d - d_t - d_l \tag{7}$$

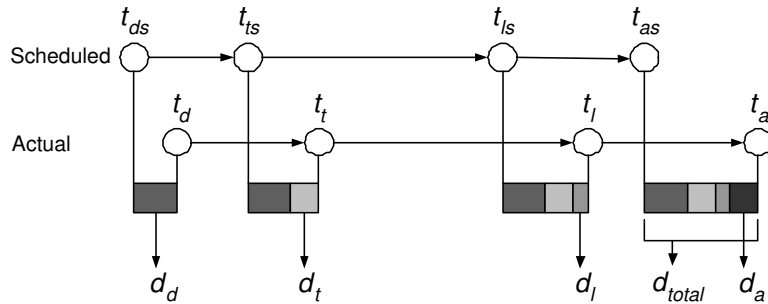$$d_{total} \quad = \quad d_d + d_t + d_l + d_a \tag{8}$$

Figure 2. Graphical representation of delay per stage of flight.

Figure 2 shows a graphical representation of how delay is attributed to the various stages of flight. As stated earlier, arrival surface delay d_a is not currently modelled and will be zero for every flight.

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VI. Results

A total of 36 simulations were run across the 4 demand sets and 9 weather days (see Figure 3(a)). The incurred departure delay, as a percentage of total delay, increases significantly from approximately 0% to 30% as demand increases and capacity decreases. As a result of the departure delay increase, takeoff surface delay decreases from 70% to 45% and enroute delay decreases from 36% to 21%. As stated earlier, ACES Build 1.2 does not currently cancel flights. Every flight must complete its flight plan regardless of the delay incurred due to congestion. When demand exceeds capacity, flights are held at their gates, and departure delay increases more rapidly than either surface or enroute delay.
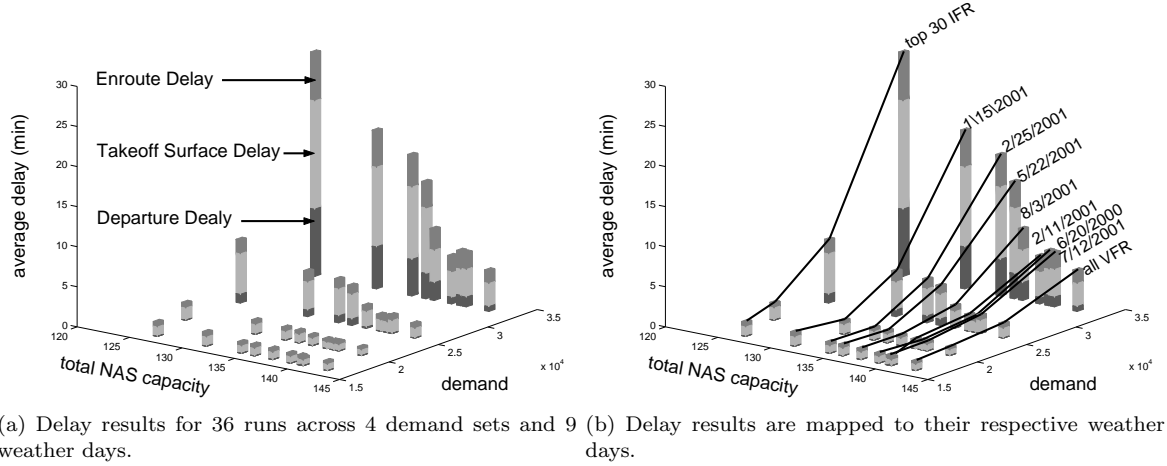

(a) Delay results for 36 runs across 4 demand sets and 9 weather days.

(b) Delay results are mapped to their respective weather days.

Figure 3. Delay surface results.

Figure 3(b) shows how the delay results correspond to their respective weather days as described in section IV. The all-VFR weather day provided the greatest NAS capacity and had the least delay. The top-30-IFR weather day resulted in the greatest delay and least capacity. The intermediate weather days, February 11, 2001, June 20, 2000, and July 12, 2001 were described as being low weather days.[3] They contributed little to delay in simulation. The data shows high NAS capacities and corresponding low NAS delays for these days. The remaining 4 intermediate weather days were characterized as days where weather contributed to delay. The data shows increasing delay with decreasing capacity, and more variability in the results for these days.
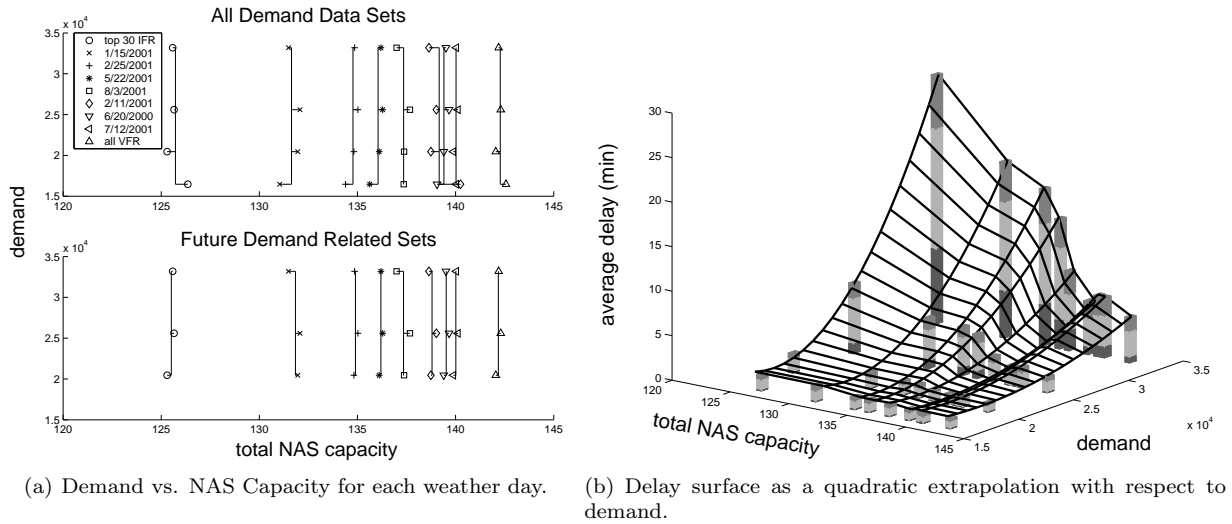

(a) Demand vs. NAS Capacity for each weather day.

(b) Delay surface as a quadratic extrapolation with respect to demand.

Figure 4. Demand Analysis Results

Figure 4(a) shows a graph of demand and total NAS capacity for each weather day. The lines represent the average capacity for each weather day. The data points show the deviation of each capacity from the average. The averaged standard deviation of the NAS capacity values for all demand sets is 0.34 total operations per quarter hour. The averaged standard deviation of the NAS capacities for the three larger demand sets with similar flight distribution is 0.18 total operations per quarter hour. The averaged standard deviation is higher when the current demand data set is included because the NAS capacity calculation is dependent on the flight demand distribution. However, a clear distinction in NAS capacity can still be seen between the weather days. It is only for the 3 low weather days that current demand NAS capacity deviates enough to cross neighboring capacity days.

When demand is compared to delay, quadratic curves produce the lowest and most random residuals; the values having a maximum of 0.32 minutes and an average of 0.05 minutes. Figure 4(b) shows what the delay surface looks like when demand data are interpolated using quadratic curves.
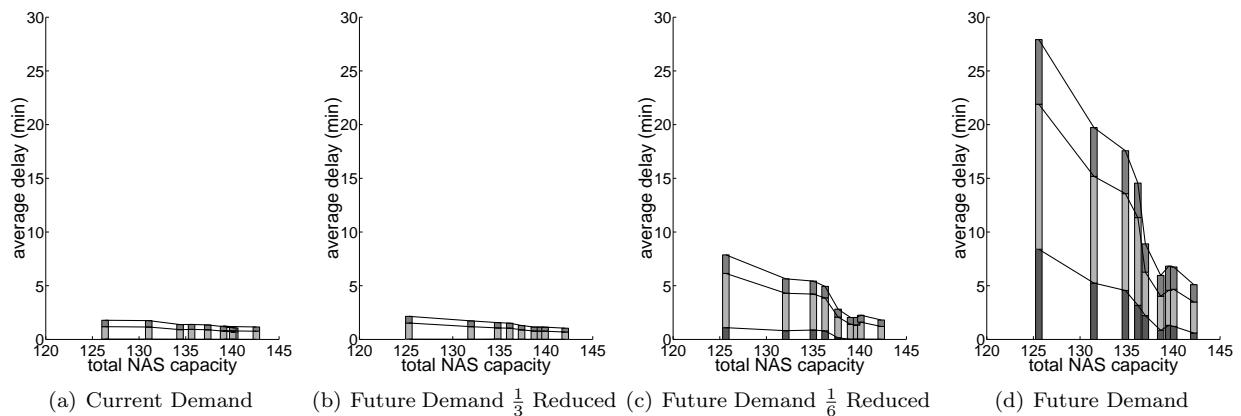

(a) Current Demand   (b) Future Demand $\frac{1}{3}$ Reduced   (c) Future Demand $\frac{1}{6}$ Reduced   (d) Future Demand

Figure 5. Delay vs. Capacity

Figure 5 shows comparisons of delay to capacity for each demand set. The data show a general linear trend. However, as demand increases, nonlinearities in the data grow larger. This suggests that other factors are influencing the results. In general the days with higher delay than the linear trend have a majority of east coast airports in IFR state. The days with lower delay have very few east coast airports in IFR state. Therefore, regional concentrations of weather located in high traffic areas may be one source of these nonlinearities.

VII.   Conclusion

This delay characterization study provides an initial quantification of the significant rise in delay experienced in the current NAS due to increasing demand. The results make a strong case for developing new airspace concepts that provide increased system capacity, and for continuing development of ACES, a NAS-wide simulation system, to assess their performance. Immediate future steps include a comparison of simulated ACES results to real world data, and an exploration of the effects of regional weather on the performance of the entire NAS. As ACES functionality increases, there we be limitless possibilities for exploring the interdependent and cascading effects that each element of the NAS has on the system as a whole.

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