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# Use of Queuing Models to Estimate Delay Savings from 4D Trajectory Precision

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*Abstract*—**The potential benefit from introducing trajectory based operations into the NAS is estimated in this paper. Delay predictions of a stochastic and a deterministic queuing model, which represent high and low levels of trajectory uncertainty, are compared. It is found that delay savings are on the order of 35% in the average case, Delay predictions from the various models are found to be strongly collinear over a wide range of congestion levels.**

***Keywords-4D trajectories; NextGen; queuing model; delay savings***

## I. Introduction

The nation's air traffic system faces a major transformation in the coming years, with the deployment of projects like the Next Generation Air Transportation System (NextGen). A cornerstone of NextGen is the use of four dimensional trajectories (4DT), with time being the fourth dimension, to enable the accurate prediction of aircraft position within a given time horizon and therefore the reduction of separations standards between aircraft. Trajectory based operations are expected to reduce excess separation resulting from today's control imprecision and lack of predictability, and enable reduced separation between aircraft, resulting in increased capacity. Operational management of 4DTs may allow more efficient control and spacing of individual flights, especially in congested arrival/departure airspace and busy runways. Overall, flight operations are expected to be more consistent, allowing operators to maintain schedule integrity without the schedule buffers that are built into today's published flight times.

However, even with the deployment of the very best 4DT trajectory precision and navigation tools, there will still be stochastic effects causing some deviation from an ideal metering schedule. Thus, the level of uncertainty in trajectory prediction can be viewed as a continuum, ranging from high levels, roughly corresponding to most current day-to-day operations, to greatly reduced ones, where (near) perfect information on trajectories is available to managers and controllers, enabling, among other things, optimal metering of flights and traffic initiatives. Between these two endpoints lies a broad spectrum, resulting from different choices of technology deployment and operational concepts. In this paper we focus in the study of the two endpoints, high and low levels of trajectory uncertainty, by employing tools from queuing theory.

In particular, the aim of this study is to compare the delay predictions of a stochastic and a deterministic queuing model for the arrival process at an airport. Such a comparison is valuable for several reasons. First, while both types of models are in widespread application in air transport, there has been little effort to systematically compare their results. The choice of which to use thus depends mainly on the "cultural heritage" of the analyst. The results of this work provide a more scientific basis for this choice. Second, the two types of models are believed to roughly correspond to different levels of 4D trajectory precision. The stochastic model reflects the current NAS, in which the level of precision is fairly low. The deterministic model represents a stylized NextGen system with perfect precision. Thus, our comparisons provide first order estimates of the benefit of implementing this particular feature of NextGen, all else equal.

## II. Background

In NextGen, as currently envisioned, the capability to fly and communicate precise 4DT trajectories will be a key criterion determining where aircraft can fly and the priority they receive. 4DT capability is defined as the ability to precisely fly an assigned 3D trajectory while meeting specified timing constraints on arrival at waypoints [1]. Aircraft with such capability will have access to trajectory-based airspace [1]. This will allow high and very high density flows that rely on controlled times of arrival (CTA) for critical resources, including entry and exit to/from airspaces, taxiways, and runways [1]. When traffic intensity is lower, it will permit autonomous operations in which aircraft self-separate and may alter their trajectories without obtaining a clearance. Aircraft without 4DT capability will be relegated to "classic airspace" in which operations are much the same as today.

As explained in the introduction, the goal of this study is to model the NAS using queuing theory in a way that these gains in 4DT performance can be related to enhanced operational control and efficiency.

Unfortunately, what is known as classical queuing theory deals to an overwhelming extent with "steady-state conditions" or "stationary conditions," i.e., with long-term equilibria which are attained "in the limit" if a queuing system is allowed to operate under constant demand rates and constant service rates for a considerable length of time. For the NAS, such steady-state conditions do not obtain in the most critical situations, in which elements or regions of the NAS are operating at demand levels near or above system capacity. The demands on the system fluctuate over the course of a day, preventing the system from reaching equilibrium [2]. As a result, the closed-form expressions provided by classical queuing theory often are of virtually no use. Many previous efforts to employ queuing theory to model NAS operations have foundered because of a failure to recognize this. In the absence of closed-form results, the analysis of dynamic queuing systems must therefore be pursued either through numerical methods based on queuing theory or through simulation.

Simulations have their place in NAS analyses, but they suffer from complexity and slow execution speed, rendering them inadequate for certain important purposes, including the kinds of problems envisioned in this study. The other alternative, numerical methods based on queuing theory, fall into three categories: (i) deterministic queuing analysis, (ii) solutions of the differential or difference equations that describe the time evolution of a stochastic queuing system, and (iii) approximation techniques, which are dominated by the diffusion approximation. In a deterministic queuing analysis, a detailed schedule of time-varying demand and a capacity schedule (possibly also time-varying) are used to compute delays, which occur whenever the demand exceeds the available capacity. This is a natural approach to use for airports [3]. Approach (ii) is directly related to classical queuing theory: the differential or difference equations describing the evolution of queuing systems over time have long been known, and are the starting point by which equilibrium results are derived. They can also describe non-stationary behavior, but it was only recently that the combination of fast computation and advanced numerical techniques made it possible to solve efficiently the large systems of such equations which are necessary to describe in a realistic way complex non-stationary queuing processes, such as those taking place in the NAS. Finally, diffusion approximation approaches focus on estimating specific aspects of the behavior of queuing systems, such as the mean or variance of queue lengths as a function of time, under more general assumptions than those of classical queuing theory. Theoretical aspects of these approaches have also been largely understood for several decades but, once again, the full practical value of these approaches has been attained only recently through vastly increased computational power and advances in numerical analysis related to solutions of systems of partial differential equations.

## III. QUEUING MODELS FOR PRECISE AND IMPRECISE CASES

We first present the stochastic queuing model we used for the low trajectory precision case, and also the deterministic one for the high precision case. Next, we provide some details about the demand data and the capacity scenarios employed in this study.

### A. *Stochastic Queuing Model*

The stochastic delay model employed in this research effort is DELAYS, developed by MIT. DELAYS is a numerical model of a large and important family of dynamic queuing systems with time-dependent arrivals. The following provides a description of the conceptual basis and of the mechanics of the model.

DELAYS originally developed by Kivestu [4] at MIT, approximates the behavior of queuing systems with a non-stationary Poisson demand process, time-dependent Erlang-k service-time distribution, n servers and infinite queuing space, commonly denoted as $M(t)/E_k(t)/n$. The model works by solving the equations that describe the evolution of the system over time. As an example consider the case $n$ = 1, i.e. the queuing system has a single server. The Chapman-Kolmogorov (C-K) first-order differential equations that describe the evolution over time of a $M(t)/E_k(t)/1$ queuing system with a capacity of $N$ customers (i.e., queuing space for $N$ – 1 customers) are as follows:

$$
\begin{aligned}
&P_0'(t) = -\lambda(t)P_0(t) + k\mu(t)P_1(t) \\
&P_i'(t) = -(\lambda(t) + k\mu(t))P_i(t) + k\mu(t)P_{i+1}(t) && 1 \le i \le k-1 \\
&P_i'(t) = \lambda(t)P_{i-k}(t) - (\lambda(t) + k\mu(t))P_i(t) + k\mu(t)P_{i+1}(t) && k \le i \le (N-1)k \qquad (1) \\
&P_i'(t) = \lambda(t)P_{i-k}(t) + k\mu(t)(P_{i+1}(t) - P_i(t)) && (N-1)k < i \le Nk-1 \\
&P_{Nk}'(t) = -k\mu(t)P_{Nk}(t) + \lambda(t)P_{(N-1)k}(t)
\end{aligned}
$$

where $\lambda(t)$ is the demand rate, $\mu(t)$ is the service rate, $i$ is the current state of the queuing system, and $P_i(t)$ is the probability of being in state $i$ at time $t$. The system has ($Nk$ + 1) states, each representing the number of "stages of work" currently in the system, as each customer introduces $k$ stages of work, due to the assumption that service times are $k$-th order Erlang.

In airport applications, DELAYS uses the number of landing and/or takeoff demands for the demand rate, $\lambda(t)$, and the capacity profile as the service rate, $\mu(t)$. DELAYS then starts at time $t$ = 0 (e.g., 3 a.m., when the airport can be said to be "at rest") with $P_0(0) = 1$ and $P_i(0) = 0$ for all $i$ > 0. The system is assumed initially to be empty (this matches perfectly with the NAS) and has negligible probability of returning to an idle state throughout the analysis period. In particular, the empty initial state is a dramatic departure from equilibrium conditions. The model then proceeds to solve the C-K equations iteratively by computing $P_i(\Delta t)$ for all system states $i$ ($0 \le i \le Nk$) and for an appropriately small time increment,

$\Delta t$, and continues by computing $P_i(2 \cdot \Delta t)$, $P_i(3 \cdot \Delta t)$, etc., for all system states *i*, until it has "stepped" in this way through a 24-hour period. Having thus computed all the state probabilities for the entire 24-hour period, it then provides estimates for the average waiting times, average number of aircraft in the queue for using the runway system, etc., as specified by the user.

Because DELAYS is an approximation of a queuing system with infinite queuing space, the number of states for which the C-K equations are solved is set to a large number from the outset. Moreover, at the end of each iteration DELAYS checks the probability of having a full queuing system. If that probability exceeds $10^{-6}$, then DELAYS adds *k* more states to the already existing ones. In this way, the system always has sufficient queuing space to accommodate all incoming demands. With the time parameter $\Delta t$ set small enough, any potential state space violation can be remedied before it affects the evolution of the system.

Most recently, the DELAYS model has been used extensively to estimate delays at LaGuardia airport under various policies involving market mechanisms for allocating landing rights [5]. Its delay estimates have been validated very successfully through a detailed comparison with actual reported delays at Atlanta and Chicago [6].

### B. *Deterministic Queuing Model*

In order to obtain results for queuing at airports under high precision cases, deterministic queuing models are used. This means that the inputs to the system, including the inter-arrival times and service rate, are deterministic. Two different versions of these models are formulated and compared to the stochastic model. One of these, which we will term the Micro Model, is based on arrival times of individual flights. The other, the Macro Model, one is based on aggregate flight demands in discrete time periods.

#### 1) *Micro Model*

In order to calculate delays a deterministic queuing analysis is used based on individual flight data. Let *F* be the set of flights, and $IS(i) \quad i \in F$ be the initial scheduled arrival time of the *i-th* flight, with the flights indexed in order of scheduled arrival (*i* = 1 for the first flight; *i* = 2 for the second flight, etc). The airport is treated as a single server, and the initial schedule of flights is obtained from ACES runs discussed below. The day is divided into discrete time periods of equal duration $\Delta$ and indexed with $t = 1,2,\ldots T$. For each time period *t* a capacity, $C(t)$, defined as the maximum number of flights that can land in that period, is provided. We translate this into minimum headway requirement between two flights, as follows:

$$H(t) = \frac{\Delta}{C(t)} \tag{2}$$

Using these headway requirements, a set of output times $AS(i) \quad i \in F$ can be created as follows:

$$\begin{aligned} &AS(1) = IS(1) \\ &AS(i) = Max\ \{AS(i-1) + H[\tau(AS(i-1))];\ IS(i)\}\ \ \forall i > 1 \end{aligned} \tag{3}$$

where $\tau(x)$ is the time period including the specific time $x$. Using these results it is possible to calculate delays for individual flights as follows:

$$Delay\ (i) = AS\ (i) - IS\ (i) \tag{4}$$

When demand exceeds capacity actual arrival times are controlled by the first term in the $Max(\cdot)$ function and equation (4) yields positive delays.

#### 2) *Macro Model*

In this model, individual flight data are aggregated to determine arrival flight demand by time period. This can correspond to an airport where there is metering to smooth out demand in any given time period. In order to calculate delays flights are put into bins of a certain time length (15 or 30 minutes, for example) and a demand $D(t)$ for each time period *t*, specifying the number of flights scheduled in that time period, is calculated. This is done so that bin 1 for 15 minute aggregation is defined as time from 00:00:00 to 00:14:59 bin 2 as from 00:15:00 to 00:29:59 and so on. Capacities for each time period, in units of flights per period, are also defined in the same way as the Micro model. As above, these are denoted $C(t)$.

In order to calculate delay the cumulative demand curve (which will be used as an input curve) and the cumulative throughput curve (which will be used as an output curve) are created:

$$\begin{aligned} &CD\ (1) = D\ (1) \\ &CD\ (t) = CD\ (t-1) + D\ (t) \end{aligned} \tag{5}$$

$$\begin{aligned} &CT\ (1) = Min\ \{CD\ (1), D\ (1)\} \\ &CT\ (t) = Min\ \{CD\ (t), CT\ (t-1) + C\ (t)\} \end{aligned} \tag{6}$$

where $CD(t)$ and $CT(t)$ are the cumulative demand and cumulative throughput at the end of time period *t*.

In order to calculate delays the area between the cumulative demand and cumulative throughput curves is calculated. This is obtained from:

$$Delay = \Delta \sum_t CD(t) - CT(t) \tag{7}$$

where, as before, $\Delta$ is the length of the time period.

Comparing the two deterministic models, it can be seen that the macro model effectively assumes that the flights arriving in any given time period are scheduled to arrive continuously and at a uniform rate; in other words, flight traffic is treated as a fluid. The macro model also closely approximates a schedule of discrete flights in which scheduled headways in any given period are constant. The micro model, in contrast, reflects the unevenness of the true schedule, and is thus expected to predict somewhat higher delays than the macro model.

## IV. MODEL COMPARISON METHODOLOGY

To compare predictions from the three models, we required a methodology that would translate identical demand and capacity information into the inputs required by each model. To increase the relevance of the comparisons, it is desirable that this information be representative of actual conditions at major US airports.

The arrival flight schedules are obtained through runs from the Airspace Concept Evaluation System (ACES). ACES is a high-fidelity simulation model of the National Airspace System. It includes models of flights, airports, airspaces, the air traffic service provider (consisting of models of the air traffic management functions), the flight decks, and the airline operational control centers operating throughout the United States [7]. We based our schedules on simulation runs for four peak and four off-peak days in 2007, a total of eight demand scenarios, assuming infinite capacity for all airports and en route sectors. The schedules, which include both commercial and general aviation flights, were developed by the FAA Air Traffic Organization to support NEXTGEN benefit studies. Since the aim of these simulation runs is to obtain the demand to the airports regardless of whether or not it can be actually served, infinite capacity is used. The output of this simulation includes:

- Landing/wheels-down day and time in UTC time zone
- Arrival day and time in UTC time zone
- Arrival airport code

From this data set, arrivals to any airport can be extracted since the simulation is done for the entire National Airspace, and the landing/wheels-down day and time in UTC time zone is used for analyzing different cases.

The capacity of individual airports is based on airport acceptance rate (AAR) values obtained from the Airspace System Performance Metric (ASPM) data base maintained by the Federal Aviation Administration. ASPM provides quarter-hour AAR values for every major US airport for every day since January 1, 2000. Clustering methodologies have been employed to extract, for different airports, representative capacity scenarios from these data [8]. A capacity scenario is a time series of AAR values extending over the airport operating day that is similar, but usually not identical, to many time series seen in the data. A scenario typically corresponds to a commonly observed weather pattern, such as the morning marine stratus and its midday burn-off in San Francisco. Scenarios 1 and 6 in Figure 1 show arrival capacity patterns that could be associated with the fog burn-off phenomenon with two burn-off times. Scenario 3 in the same figure has capacity profile similar to those of scenarios 1 and 6 early in the day, but stays with low capacity throughout the day. Note that scenarios 1 and 3 feature a pattern of oscillation with a periodicity of one hour. This is actually an artifact of the reporting system, which converts hourly rates to quarter-hour ones but also requires integer values.

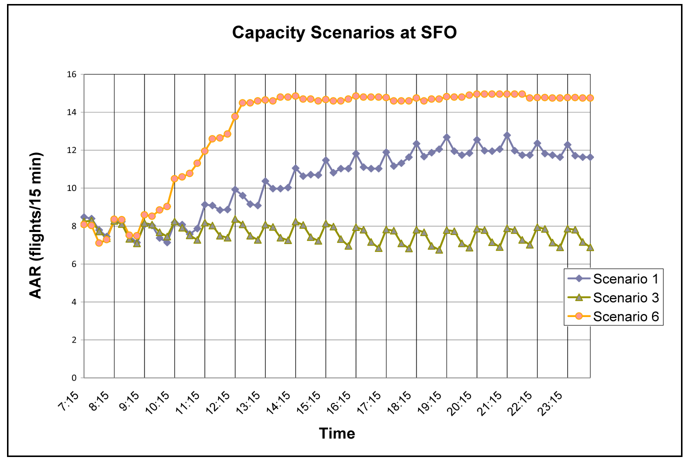


Figure 1. Examples of capacity scenarios at SFO

The Low Precision (DELAYS Model), and the High Precision (Micro and Macro Models) are used in order to calculate delays for the following airports:

- Atlanta (ATL) – 5 capacity scenarios
- Boston (BOS) - 6 capacity scenarios
- Chicago (ORD) - 5 capacity scenarios
- Dallas (DFW) - 5 capacity scenarios
- Miami (MIA) – 4 capacity scenarios
- New York (LGA) - 5 capacity scenarios
- San Francisco (DFW) - 6 capacity scenarios

Model predictions were compared in two ways. First we considered the predicted average delay per flight. Next, we compared daily delay time profiles. In order to so the latter, the delays should be allocated to time bins in the same way. As discussed in [9], various allocation schemes are possible. Here we follow the method used in the DELAYS model. To implement this method in the deterministic Micro model, individual delays are then accrued in time bins of 15 minutes, with the delay in each time bin calculated by adding up the delay within that time period of the flights that joined the queue during this time period. This means that if an aircraft arrives at the airport in a certain time period, is queued and then lands in a different time period, the total delay of this aircraft will be assigned to the time bin it wanted to arrive at the airport. In the Macro model, this quantity is measured as the area in between the segments of the cumulative demand and cumulative throughput curves corresponding to a particular time period. In the case of LGA, the analysis was performed on an hourly time scale rather than a 15-minute one. This is because LGA has slot controls imposed on an hourly basis, and capacity scenarios were specified accordingly.

## V. RESULTS

We first compare predictions for average delay per flight. Fig. 2 compares predicted delays per flight from the micro deterministic and stochastic models for all 288 cases, each corresponding to capacity profile at a given airport, and a demand scenario for that airport. In this plot, data points corresponding to different airports are plotted in different symbols. The first notable result is simply the magnitudes of the delays predicted by either model, which in several cases exceed 2 hours per flight. Inspection of the symbols reveals that all of the cases in which predictions exceed 100 min are for one airport—which turns out to be LGA. Further inspection of the data reveals that they correspond to two capacity scenarios featuring dramatic reductions in capacity for extended periods during the day. These scenarios together correspond to only about 4% of the days at LGA. In reality, delays on such days are typically mitigated by massive flight cancellations. Moreover, although the eye is naturally drawn to these extreme cases, delay predictions are less than 10 minutes in 70% of the cases.

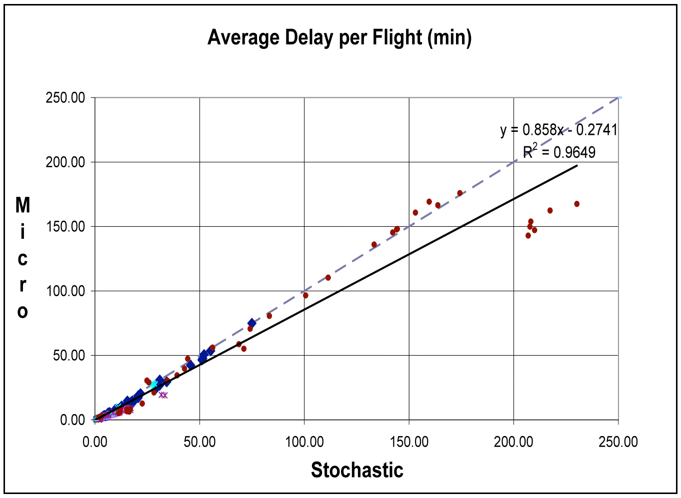


Figure 2. Comparison of DELAYS and Micro models (LGA Observations Included))

Next we note that the predictions of the two models are generally fairly close to one another, as indicated by the proximity of most points to the dashed line of equality. The major exception is a the set of six points—all for LGA observation--for which the stochastic model prediction exceeds 200 minutes while the deterministic prediction is around 150 minutes. Additionally, the deterministic predictions are virtually all below the stochastic ones, with the major exceptions again a set of LGA observations.

The unusual behavior of the LGA points is the result of an approximation that is used to calculate delays in the stochastic model. In this model, the delay for flights entering the queue in a particular time period is based upon the capacity in that time period. When queues are very long and capacity variation is pronounced, this may introduce a substantial error, on the high side if capacity increases after queue entry, or the low side if it declines. Work is ongoing to address this problem in the stochastic model.

To eliminate any distortions that may result from this problem, we eliminated the LGA results, and re-plotted the data, as shown in Fig. 3. For the non-LGA data, best fit line relating the deterministic to the stochastic model has a slope of 0.90 and an intercept of -0.84. In other words, delays under the deterministic assumptions can be obtained by subtracting 10% from the stochastic prediction and then another 0.8 minute. The $R^2$ of 0.96 implies that the fit of this relationship is very good.

This result has both a substantive and a methodological implication. Substantively, it quantifies the value of increasing determinism that can result from 4DT trajectory precision. If such precision allows airport capacity to be fully utilized in busy periods, without excess separation or idle periods resulting from the failure to promptly deliver traffic, we can expect delays to be reduced by the quantities stated above. The methodological implication is that the deterministic model, which is computationally extremely cheap, can be used to give a good approximation of the first-moment predictions of the more computationally expensive stochastic model.

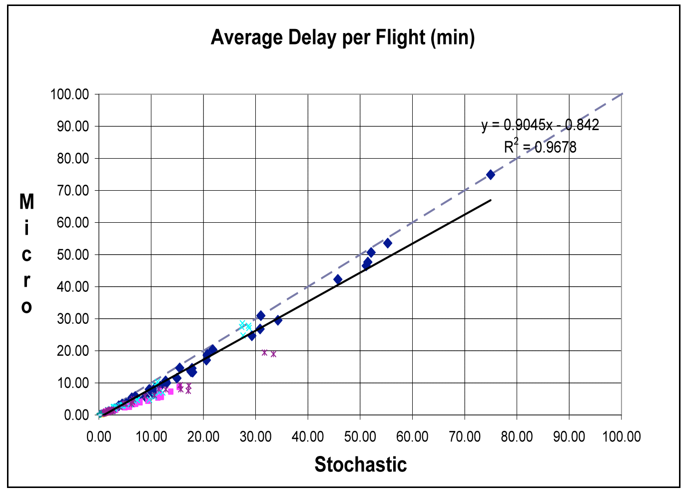


Figure 3. Comparison of DELAYS and Micro models (Without LGA Observations)

Fig. 4 compares predicted average delays from the macro and micro deterministic models. Linear correlation is extremely strong, with the macro delays slightly, but consistently, below those from the micro model. This is expected because the schedule is slightly smoothed out in the macro model, with arrivals within every 15-minute time period are scheduled at regular time intervals. The pay-off from this minimally invasive metering is to reduce delay about 4%, plus 1 minute.

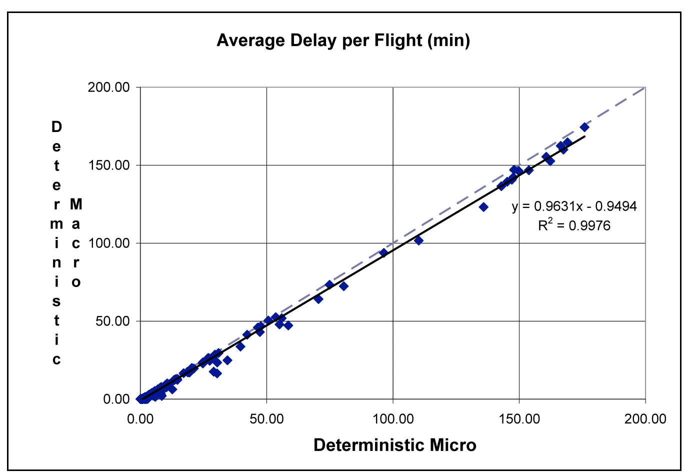


Figure 4. Comparison of Micro and Macro models

Finally, comparing the deterministic macro and the stochastic (with LGA observations excluded), we obtain a reduction of 12%, plus 1.5 minutes, as shown in Fig. 5. Taking an average over all the non-LGA observations, this implies a delay reduction from 6.4 to 4.2 minutes—about 35 percent.

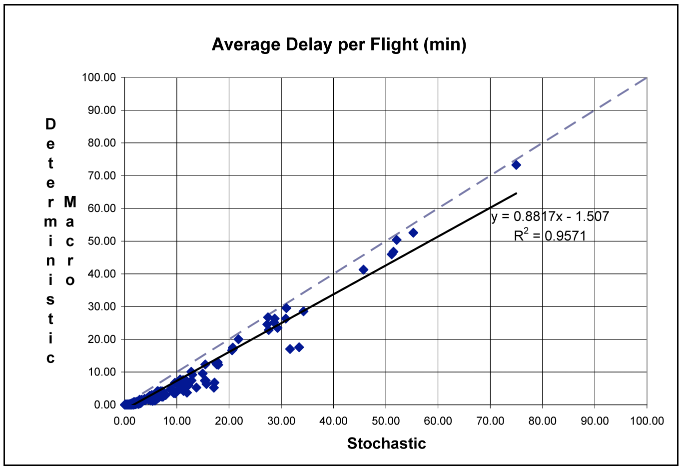


Figure 5. Comparison of DELAYS and Macro models (Without LGA Observations)

We next consider delay profiles across the day predicted by the different models. These profiles can be compared for any of the 288 observations in our data set, from which we choose a few for purposes of illustration. Fig. 6 shows an example from Boston Logan with low delay (note that these figures present aggregate—not average—delay for flights entering the queue in a given time period). Aside from the obvious scale difference, the delay profiles predicted by the three models are similar. The macro model predicts zero delay for many time periods, indicating that capacity usually exceeds demand. Bunching of the schedule leads to some delay for the micro model, while the Poisson process assumed in the stochastic model yields even more delays. The peak delay periods are not perfectly aligned, with the more common, but not universal, tendency for the deterministic models to lead the stochastic one in recovering from a congested period. Fig. 7, based on a moderate delay day for Atlanta, also shows this pattern of earlier recovery under the deterministic models. In this case, the result is that the airport is able to fully or nearly recover prior to the next busy period under the deterministic models, but not according to the stochastic one. This results in progressively greater disparity in predicted delays as the day goes on. Fig. 8, a high delay SFO case, tells a similar story, resulting in much higher delays in the afternoon period under the stochastic model. Another interesting contrast between Fig. 8 and Fig. 6 is the closer agreement between the two deterministic models in the former. This illustrates that demand smoothing can change low delays into no delays, but has little effect when demand-capacity imbalances become severe. Finally, Fig. 9—an extremely high delay case from LGA—illustrates the difficulty with the stochastic delay approximation when queuing becomes extremely severe. The huge delay peak predicted by the stochastic model results from flights arriving into the queue when capacity is very low. Under the approximation used by that model, this low capacity is assumed to persist over the (very long) period these flights remain in the queue.

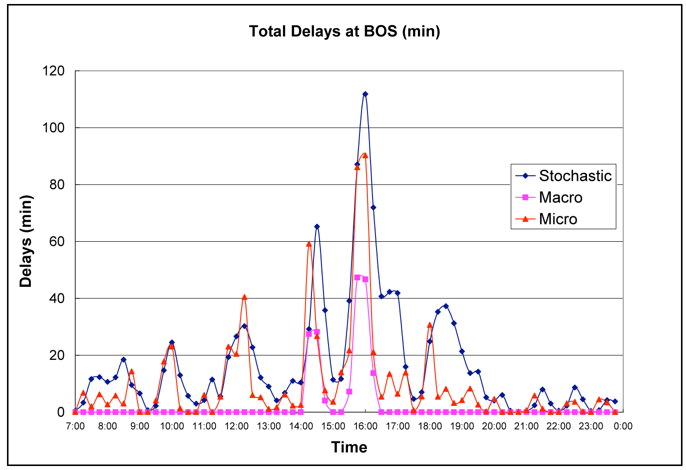


Figure 6. Delays at BOS under capacity scenario 1 on an off-peak day

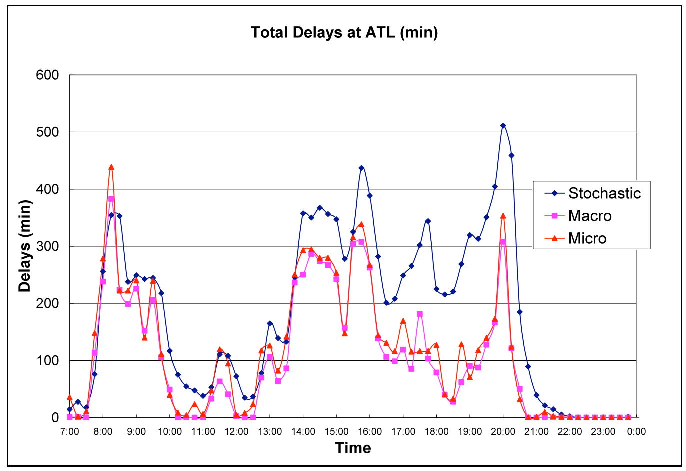


Figure 7. Delays at ATL under capacity scenario 3 on an off-peak day

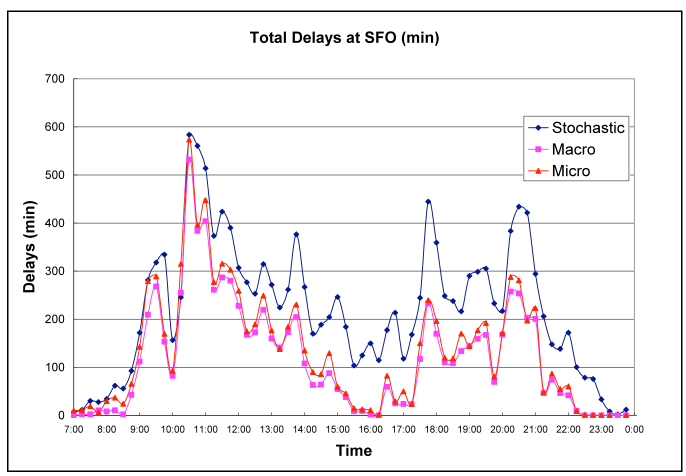


Figure 8. Delays at SFO under capacity scenario 3 on a peak day

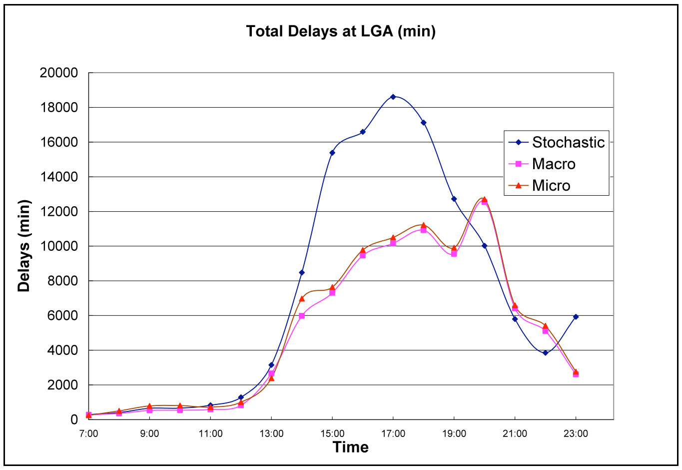


Figure 9. Delays at LGA under capacity scenario 5 on a peak day

## VI. CONCLUSIONS

We have compared delays predicted by three queuing models across a wide range of demand and capacity scenarios at seven major US airports. Comparing the predictions of these models does more than satisfy idle curiosity: it helps assess the potential benefit from introducing greater determinism into the NAS, as precise 4DT navigation should do. Our results show that this change alone—without any difference in capacity—could reduce delays considerably—on the order of 35% in the average case when the baseline delay is around 6 minutes.

The delay predictions between the three models are linearly related over a wide range of values. The difference in average delay predicted can be well-approximated as a constant on the order of 1 minute and a fraction of the stochastic delay on the order of 10%. Thus the absolute delay difference increases as delay becomes more severe, while the percentage delay difference decreases. These differences are tangible but not game-changing. It is probable that other benefits or 4DT precision navigation, such as reduced separation requirements leading to greater capacity, will have a greater impact.

The comparisons presented here are between extreme cases—a highly random Poisson process on the one hand and a fully deterministic process on the other. They also involved single queues. The models for such cases are well-established. It is far more challenging to consider intermediate levels of stochasticity and networks of queues. Such cases are far more representative of the future NAS, in which trajectory adherence will be imperfect and in which aircraft will move through a succession of congestible resources. Work to model such cases as stochastic queuing networks is ongoing.

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## AUTHOR BIOGRAPHIES

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