MODELING DELAYS AND CANCELLATION PROBABILITIES TO SUPPORT STRATEGIC SIMULATIONS

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Abstract: Modeling delays and cancellation probabilities is important for strategic-level decision support tools in aviation planning. In this paper, we introduce models for average delays and cancellation probabilities that distinguish between carriers but do not rely on proprietary information. The models were developed for a strategic simulation to determine the effects of congestion management schemes at LaGuardia Airport, including government regulations, administrative controls, and congestion prices. We also demonstrate the use of the models to help determine the appropriate number of hourly slots to offer in a hypothetical slot auction.

Introduction

Delay modeling for air transportation systems poses several unique challenges. Flight movements are ultimately tied to schedules so flight arrivals at airspace system queues do not follow distributions typical for standard queuing systems. While most statistics are measured and stated relative to flight delays, the ultimate performance measure should be relative to the system users: the passengers. Finally, the airlines routinely exercise a powerful control knob, the flight cancellation, to keep the impact of delays in check. Thus, a comprehensive approach to flight performance must include both metrics for flight delays and metrics for flight cancellation propensity. Another factor to consider in approaching delay modeling involves the scope across several possible dimensions. For example, one could be interested in daily, monthly or annual delay metrics for an individual flight, an airline or all airlines.

Background

In this paper, we describe an approach to generating estimates of both average flight delay and flight cancellation probabilities. This approach was specifically developed to support a strategic simulation conducted in November, 2004, by NEXTOR, the National Center of Excellence for Aviation Operations Research. This strategic simulation was part of a larger project funded by the U.S. Department of Transportation (Federal Aviation Administration and Office of the Secretary) to investigate approaches for allocating capacity at LaGuardia Airport (LGA). On January 1, 2007, the legislation authorizing the "High Density Rule" (HDR) will expire. The HDR currently provides a mechanism for limiting the number of arrival and departure slots at LGA and for allocating them to airlines. The NEXTOR project is investigating several alternative approaches to slot allocation including administrative controls, congestion-based landing fees and auctions.

A distinctive and important aspect of this project involves the use of strategic simulations. Strategic simulations are experiments in which actual decision makers participate in a simulated exercise. These simulations can provide substantial value in three areas. First, they provide a reasonably realistic projection of the impact of various planned procedures and tools. It is often the case that such procedures lead to impasses or very difficult-to-resolve issues. These uncomfortable situations actually are the source of the second advantage of strategic simulations: the ability to uncover the need for procedures, tools or rules that were completely unanticipated at the beginning of the experiments. This distinguishes such simulations from exclusively computer-based simulations and analyses. The third very important role they play is in the education of the participants and others observing and studying the strategic simulation. By observing and recording the unfolding of events and the players' subsequent decisions, one gains a deep and intuitive understanding of the issues involved.

The simulation for which our models were developed involved approximately 100 participants. There were six major game "players" consisting of teams from 4 airlines, the Federal Government and the Port Authority of New York and New Jersey, which operates LGA airport. Other participants included representatives of other airlines and airports, the Air Transport Association and various experts from academia, industry and government. The game projected the participants to a hypothetical setting in November of 2007. The baseline scenario was an LGA schedule involving approximately 1400 total operations (arrivals and departures). The airline teams adjusted their schedules in response to various government controls put in place. These controls involved Federal Government regulations, administrative restrictions and congestion-based fees. The airline teams made a total of 5 schedule adjustments. The role of our models was to project 3-month delay and cancellation statistics associated with each new schedule produced. Fast response time was an important requirement for the models since it was important to reduce the amount of idle time between game iterations. The game manipulated data at the individual flight level. However, the input to the models was an hourly vector of scheduled arrivals and departures and the output consisted of hourly statistics on arrival and departure delays and flight cancellation probabilities. The overall delay statistics could vary by airline since the distribution of scheduled operations over the day could vary by airline. Similarly, flight cancellation probability could vary by airline; however, there was also a special procedure for adjusting airline flight cancellation probabilities based on the propensity of each airline to cancel flights.

We describe, as well, the use of the models we have developed for a second related application. The strategic simulation for which these models were developed did not address an important alternative being considered under the NEXTOR project: slot auctions. Slot auctions for LGA are the subject matter of on-going research and will also be considered in future strategic simulations (for background on slot auctions see [1]). Under the slot auction option, the period of time when LGA is open would be divided into a sequence of time buckets. (Time bucket width is a question currently under consideration – it is probably safe to assume the width will be between 15 minutes and 1 hour.) A maximum number of arrivals and departures (slots) would be associated with each time bucket. The auction would proceed by allowing airlines to bid for these slots. Each time bucket would represent a different product in the sense that the final price would vary by time bucket. A fundamental question in executing such an auction is defining the number of slots in each time bucket. Like most airports, LGA has , of course, established a set of engineering standards for maximum arrival and departure rates. However, these rates vary with runway configuration, weather, etc. We describe herein how our models can be applied to set appropriate levels for scheduled arrivals and departures given these variable arrival and departure rates. Unlike the first application, this work has not produced a final set of answers, yet. In this paper, we describe the appropriate model formulations and give some sample solutions.

In the next two sections, we describe the cancellation and delay models separately. Following that, we offer more details about how these models were integrated to support the two applications. Finally, we provide results and conclusions.

Cancellation Model

When faced with significant congestion and delays, and in some scenarios actual monetary costs associated therewith, airlines can choose to cancel certain flights. The cancellation of a flight is an extreme, but sometimes necessary, powerful and appropriate measure. In order to determine the impact of congestion reduction strategies, it is then important to be able to estimate the extent to which airlines will utilize cancellations. A number of models have been developed to assist airlines in deciding what flights, if any, to cancel when long delays are anticipated (see, e.g., [2], [3] and [4]), while extensive records are available on the rate at which different airlines cancel flights and the circumstances under which they do so. In the context of this paper, and at any level where multiple airlines and their respective operating strategies are in play, it is not reasonable to assume that such information is available. Therefore, we approach the modeling of cancellations from a macroscopic point of view. We assume that in the aggregate, airlines use cancellations to mitigate against unacceptable delays. We specify, in a model calibration step, a single delay threshold U, and choose those flights to remain on the schedule that produce the maximum throughput without exceeding this delay threshold (by maximizing the number of flights that remain in the schedule we minimize the number of cancellations).

The modeling mechanism is a network flow model [5]. The hourly scheduled demand is computed from the individual flight schedules submitted by each airline. The vector of airport arrival capacity for each hour is necessary to estimate cancellations. In our LGA application, we considered four possible scenarios of hourly arrival capacity, which are shown in Figure 1. The capacity scenarios are derived from statistical cluster analysis using historical data of arrival capacity at LGA (see [6] for details). Each scenario is associated with a probability, given in parentheses in the figure, of occurrence on any given day. This value reflects the proportion of days past when the hourly arrival capacities at LGA matched closely with the respective scenario.

Given the hourly arrival demand and capacities (corresponding to a particular scenario) the cancellation probability is computed by using a linear optimization model described as follows. Inputs to the model are the following: (1) hourly scheduled demand D_t, $t = \{1, \ldots, 24\}$; (2) hourly arrival capacities C_t^q corresponding to a scenario $q \in \{1, \ldots, Q\}$, where Q is the total number of scenarios considered (four in our analysis); (3) upper bound on delay faced by any flight, U. This last parameter was used to calibrate the model so that the cancellation probabilities obtained from the model matched with those observed from aggregate real data.

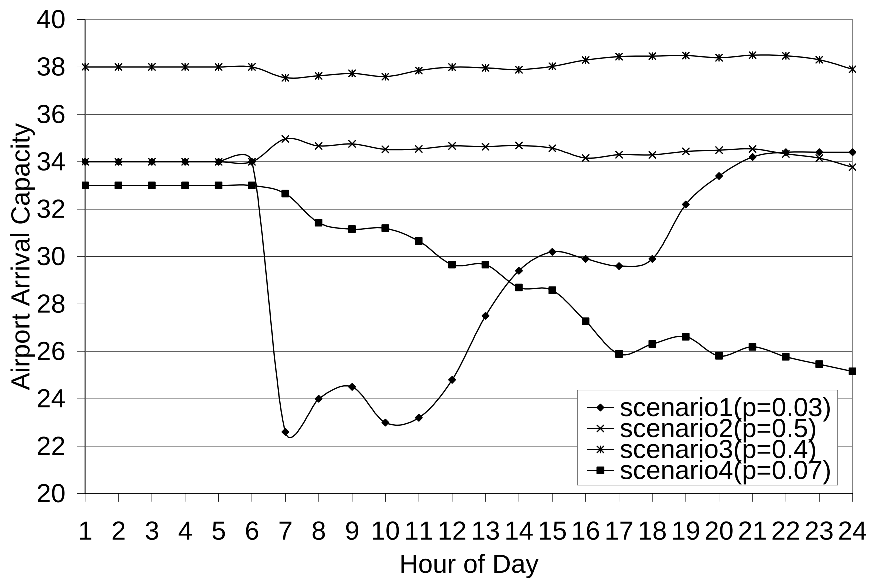

Figure 1. Capacity scenarios and their probabilities of occurrence on a given day at LGA.

Figure 2 illustrates the key parameters and decision variables used in the model. The total planning horizon is $T = 24 + U$ hours. The numbers in parentheses are the arc capacities. The capacities of the horizontal arcs – W_t^q – are given by the sum of airport capacities during the hours $t+1, .., t+U$, i.e. $W_t^q = \sum_{t+1}^{t+U} C_t^q$. This limits the delay faced by any flight to U hours. The arc flows under a capacity scenario $q \in \{1, .., Q\}$ are given by the decision variables X_t^q and Y_t^q. The total throughput is given by $\sum_t X_t^q$.

The objective function is to maximize $\sum_t X_t^q$.

The arc flows must satisfy the capacity constraints as follows:

$$0 \le X_t^q \le D_t \qquad (1)$$

$$0 \le Y_t^q \le W_t^q \qquad (2)$$

$$0 \le X_t^q + Y_{t-1}^q - Y_t^q \le C_t^q \qquad (3)$$

All three of these constraints are required over the domain $t \in \{1, .., T\}, q \in \{1, .., Q\}$.

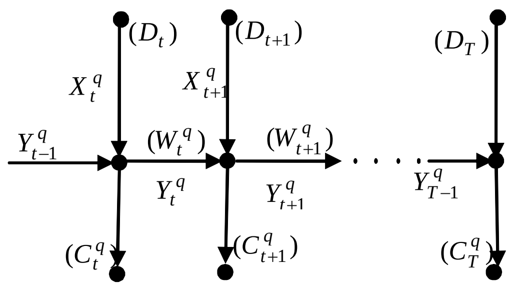

Figure 2. Maximum flow network formulation of the cancellation probability model.

Although the model is formulated as a linear program, integer solutions are guaranteed since the underlying constraints have a network flow structure (see [5]). The cancellation probability under scenario *q*, denoted by P_{cnx}^q, is given by

$$P_{\text{cnx}}^q = \frac{\sum_{t=1}^{24} (D_t - X_t^q)}{\sum_{t=1}^{24} D_t} \qquad (4)$$

Taking the expectation across scenarios, the cancellation probability, given a demand vector at LGA, is given by $\sum_{q=1}^{Q} \left(P^q\right)\left(P_{\text{cnx}}^q\right)$, where P^q is the probability of occurrence of capacity scenario *q* on any given day.

After calibrating the above model with historical data on demand and cancellations at LGA, the maximum delay parameter *U* was set to 2 hours. Furthermore, it was observed that on days with low congestion and delays at LGA, flights bound toward LGA faced approximately a 3% chance of being cancelled. This may be attributed to several factors in the NAS not directly related to the operating conditions at LGA, which result in flight cancellations. Thus the probability of cancellation is given by:

$$P_{\text{cnx}} = 0.03 + \sum_{q=1}^{Q} \left(P^q\right)\left(P_{\text{cnx}}^q\right) \qquad (5)$$

It was observed that the cancellation propensity varied across airlines. Some of the major airlines at LGA had a tendency to cancel a lesser proportion of flights than the average cancellation probability. We used past data of cancellations to compute airline-specific propensities. During the strategy simulation, the participating airlines were provided with an option to re-scale their cancellation propensity. The cancellation probabilities of individual carriers were adjusted by multiplying their respective cancellation propensities with the average probability. Thus, if some airline decides to reduce their cancellation propensity, this would result in fewer cancellations by that airline. This would affect, potentially increase, the delays of all other carriers. Although airlines were provided with the flexibility to adjust their cancellation propensity, none of the participating airlines changed their traditional propensities during the simulation. The typical reason given was that this propensity was intimately tied to corporate processes and systems and, thus, was difficult to change. In our model, the departure cancellation probability is the same as the arrival cancellation probability, from conservation of mass considerations.

Delay Model

The classical steady-state results of queuing theory usually cannot be applied to runway queues. During the course of a typical day demand and service rates may vary significantly over time and the use of steady-state expressions often yields very poor approximations [7]. Moreover, demand rates often exceed service rates for periods of time that may last for as long as a few hours at some major airports. Steady-state results do not, of course, apply when the demand rate exceeds the service rate.

To overcome these problems, we have used a stochastic and dynamic queuing model to estimate delays due to runway congestion. DELAYS© is an analytical queuing model, *not* a simulation, developed at MIT [8, 9]. It views any complex of runways as a queuing system. The capacities (service rates) for landings and for takeoffs (or, when more applicable, the total capacities for arrivals and for departures) are given inputs and may vary dynamically over time in response to such factors as changes in runway configuration in use, weather conditions, noise-related policies or changes in traffic mix. Typically, the user specifies the capacity for each one-hour period of the day, but time can be subdivided into periods smaller than one hour, if desired. The demand rates for landings and takeoffs are also dynamic quantities and are assumed to be given inputs. Given the hourly (or other time-unit) demand and capacity profiles, the model estimates the delay incurred by aircraft on landing and on takeoff as a function of time throughout the course of a day or other specified period of time.

DELAYS© is based on the work of Koopman [10], Kivestu [8] and Malone [9]. It approximates runway complexes as queuing systems with non-homogeneous Poisson arrivals and Erlang service times ($M(t)/E_r(t)/1$, in the notation of queuing theory) with the order r of the Erlang service times chosen with reference to the coefficient of variation of the service times at the runway. Beginning with a set of initial conditions at t=0, DELAYS© solves iteratively, for t equal to Δt, $2\Delta t$, $3\Delta t$,…, a (possibly large) set of difference equations that describe the evolution of the queuing system over the entire period of interest. The quantities computed are the probabilities, $P_n(t)$, of having n "customers" (aircraft) in the queuing system at time t for n = 0, 1, 2, 3,…. The model adjusts internally the update interval Δt and the number of equations to be solved at each update depending on the model inputs at hand. It is extremely fast, taking advantage of an accurate approximation scheme developed by Kivestu [8] – for details see [9].

One major advantage of this approach is that the entire probability distribution for the number of aircraft in the queue is computed for all values of t. Thus, in addition to the usual measures of mean queue length, mean waiting time, etc., DELAYS© provides estimates of distributive measures of interest, such as, for example, the fraction of arrivals and/or departures that have to wait more than 15 minutes for access to the runway system.

In our examples, we have only modeled runway arrivals; departure delays are computed separately, as discussed later. Similar to the cancellation model, the delay results are very sensitive to the runway capacity vector, so we use multiple runs of the delay model with the same capacity profiles as before, and aggregate the results.

Applications

As noted earlier, the two applications that the models have been used for are delay and cancellation estimates under congestion reduction schemes for the strategic game, and determination of the appropriate number of slots to offer in a hypothetical auction. This section describes these applications in more detail, and illustrates how the cancellation and delay models were employed in each case.

Strategic Game

For each round of the strategic simulation game, players representing airlines, either individually or in some cases as a form of consortium, would submit proposed schedules in the form of a vector of hourly arrivals at LaGuardia. These demands were summed, and this represented the aggregate, nominal schedule. This was the input to the cancellation model. For any particular input vector, a set of four capacity vectors was used, as already described (Figure 1). It was generally true that the maximum delay for any given schedule would exceed the threshold U=2 hours specified above, for at least the most extreme capacity scenario(s). Thus, the responsibility of the cancellation model was to determine how many of these flights, by airline, should be cancelled, taking into account the rough measure of airline cancellation propensity mentioned above. Final results were obtained by taking expectations across these scenarios. Because of conservation, departure cancellations were the same as arrival cancellations.

One of the hypothetical options considered for congestion management at LGA was a fee structure imposed for cancellations and delays in excess of 15 minutes, supposedly as a result of a "passenger bill of rights" (PBR) imposed by Congress. The results of the cancellation model were used to directly compute that portion of the fees imposed on each airline as a result of cancellations.

The nominal schedule was reduced according to the results of the cancellation model, and this formed the vector of inputs to the delay model. Again, for any particular input vector, four capacity profiles were possible, each with different relative frequencies. Thus, four runs of the delay model were performed, one for each capacity scenario, and the results were aggregated.

The airport experiences departure delays as well as arrival delays, which could also have been modeled as a stochastic queue. However, we followed a different approach that takes advantage of historical data on the relationship between arrival and departure delays at LaGuardia. A delayed arrival generally implies a delay in the corresponding departure. Statistical information[1] for the years 2000 – 2004 show a very strong positive correlation ($\rho = 0.90$) between average arrival and departure delays at LGA, as illustrated in Figure 3. Thus, aggregate departure delays were modeled as a linear function of aggregate arrival delays according to the following simple linear regression model, which is shown graphically in the figure:

$$w_d = 0.9763 w_a + 3927.8 \qquad (6)$$

where w_d and w_a are the departure and arrival delays, respectively.

[1] Data source: FAA – ASPM website http://www.apo.data.faa.gov/

Because of the extensive distribution outputs available from the delay model, we were able to calculate the average arrival delay of those flights whose delay exceeded 15 minutes. This seemingly esoteric statistic (for arrivals and, modified as above, for departures) was used to compute delay costs to individual airlines under the hypothetical PBR case described previously. Directly, of course, this model provides only aggregate delay statistics across all airlines; we pro-rated these results according to each airline's relative stake in each hour of the schedule to estimate results for individual airlines.

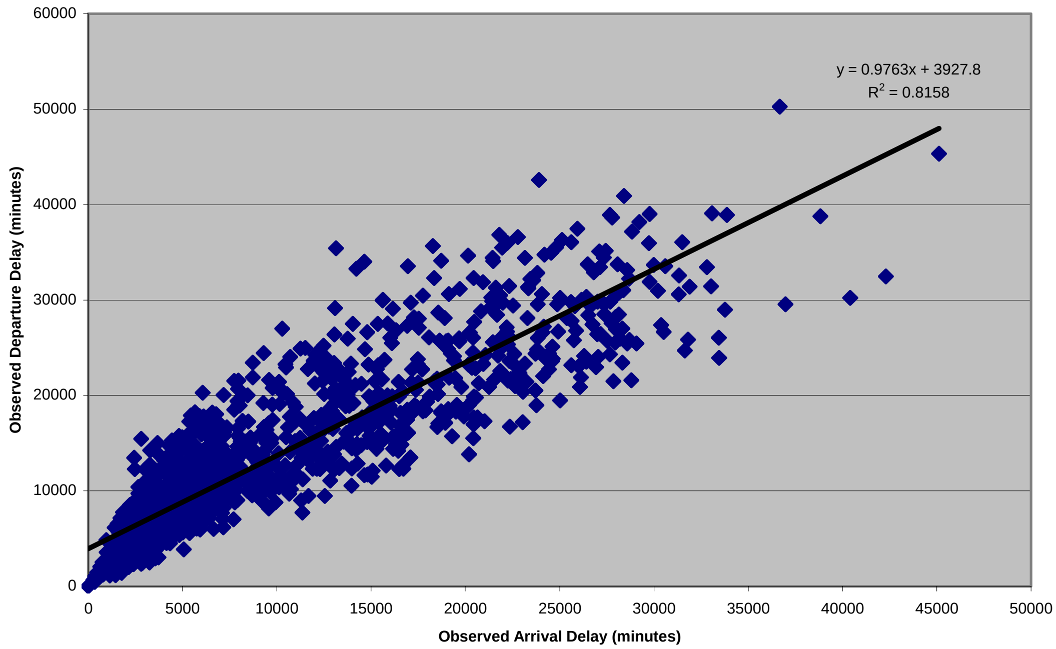

Figure 3. Relation between arrival and departure delays at LaGuardia.

This is a somewhat coarse estimate, since delays (particularly large ones) might occur in time bins later than the affected flights were scheduled for. However, the costs for each airline were summed across all hours, and this is the highest level of resolution this particular modeling context would allow. Figure 4 shows the total scheduled hourly arrival demand and average queuing delay during three phases of the strategy simulation game. Also shown in the figure are the expected cancellation probabilities in each case. In all three cases, delays become significant in the morning hours when demand first peaks. Demand stays above 35 arrivals per hour for most of the time, and frequently surpasses the VFR operating capacity at LaGuardia – 38 arrivals per hours. Therefore the average queuing delay triggered by the morning peak continues to increase until late in the evening, after which it subsides due to reduction in demand. In Phases B and C, the morning peak hour demand is considerably less than in Phase A, thus resulting in lower average delays through the rest of the day. The cancellation probability is high in Phase A due to high demand. This value matches closely with the average probability of flight cancellation during the months of October and November in 2000, when the actual daily demand at LGA was very high and close to the level assumed for Phase A of the strategy simulation. The cancellation probability for Phase C is higher than for Phase B because of higher total demand, and a similar hourly profile.

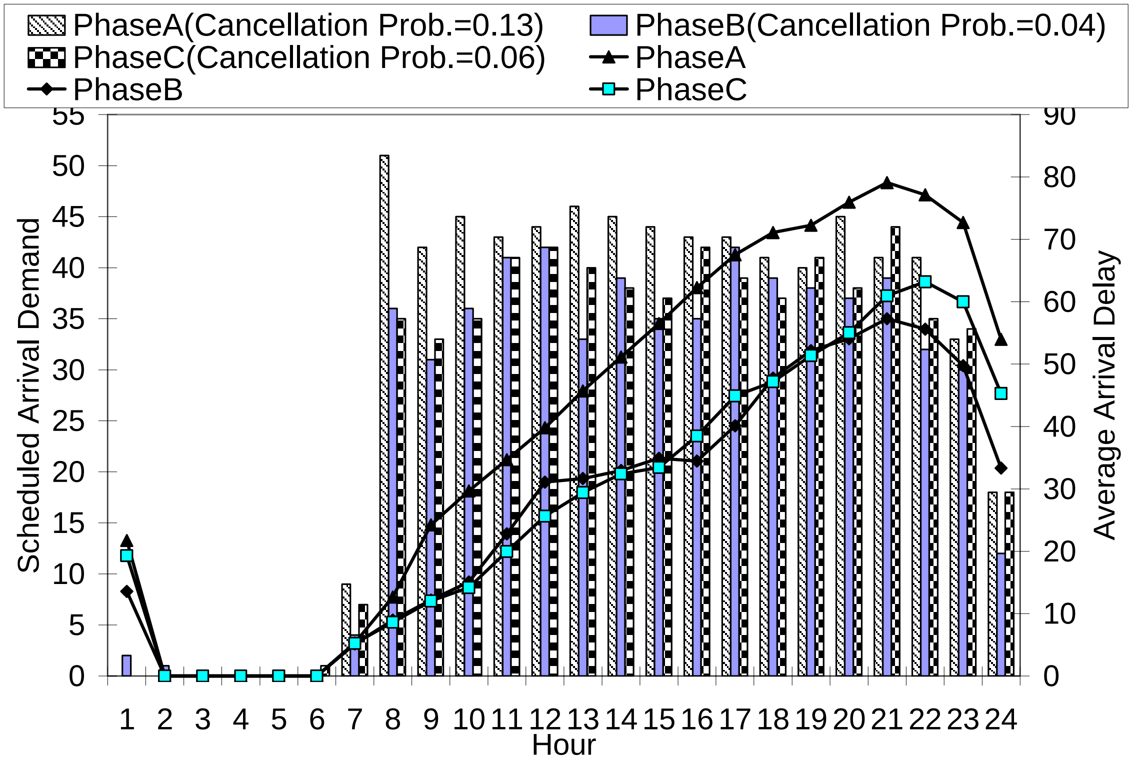

Figure 4. Demand, delay, and cancellation probabilities.

Slot Auctions

Arrival (or departure) slots during different hours of the day are usually valued differently by airlines. One reason for this is that passenger demand varies with time of day; hence airlines tend to schedule more flights during peak hours than during the rest of the day. The goal of this exercise is to take these changes in valuation into account when determining the appropriate number of slots to auction.

While the simplest menu of slots for auction might involve the same number of slots in every hour, there are important congestion-related reasons why this may not be wise. In particular, queues formed early in the day tend to persist throughout the day, so that the marginal effect of exceeding capacity early is greater than if this were to happen later in the day. Second, during any given hour, the marginal impact of additional arrivals (or departures) during congested periods increases, due to the well-understood non-linear nature of queuing delays.

Given the values of slots during different hours, we formulate a linear program to determine the appropriate number of arrival slots during each hour, by maximizing the total value of the slots while keeping the average delay and cancellation probability below certain limits. The math programming formulation of the LP is similar to that of the cancellation probability model (see Figure 2) with additional variables and constraints as described below.

The hourly demands, D_t, are decision variables in this problem. The objective function is to maximize the value of scheduled demand $\sum_t V_t D_t$, where V_t are the anticipated values of slots during different hours of the day. It is important to note that the true values will be revealed by the auction process and will only be known after the auction is completed. However, the number of available slots in each hour must necessarily be somehow determined prior to the auction. It might then be possible to determine approximate values ahead of time through the use of a strategy simulation game or some form of economic analysis. For example, in the November 2004 game, several iterations of schedule modifications (carrier actions) and congestion prices (government actions) were conducted. In any event, we assume that the set V_t would be determined in one of these ways.

In addition to the arc capacity constraints (1) – (3), the following side constraints are now necessary:

$$\sum_{q=1}^{Q} P^q \sum_{t=1}^{24} (D_t - X_t^q) - \eta \sum_{t=1}^{24} D_t \le 0 \qquad (7)$$

$$\sum_{q=1}^{Q} P^q \sum_{t=1}^{24} Y_t^q - \mu \sum_{t=1}^{24} D_t \le 0 \qquad (8)$$

$$D_{\min} \le D_t \le D_{\max} \qquad (9)$$

These constraints must hold for the domain $t \in \{1,\ldots,T\}; q \in \{1,\ldots,Q\}$.

Constraint (7) imposes a limit η on the overall cancellation probability. Similarly, constraint (8) imposes an upper bound μ on the average delay. Note that the delay thus obtained is deterministic queuing delay. Constraints (9) specify the minimum and maximum number of slots available during any hour. Suitable values of these bounds must be chosen based on minimum and maximum operating capacities of the airport.

As mentioned earlier, the delay obtained from this model is the deterministic queuing delay. We would prefer to directly bound the stochastic delay from the model described in a previous section, but this introduces complicated nonlinear constraints. Instead, we used an iterative heuristic whereby the optimum demand vector, D_t, from this model was used as the input to the stochastic delay model described above, and the parameter μ was adjusted until the results from both models matched sufficiently.

Figure 5 summarizes the experimental results from this application. The slot values are based on congestion prices that were set during one stage of the strategic simulation. Note that the magnitudes of the values are not important in the optimization model, only their relative values. In the figure, we plot the ratio between hourly slot values (or hourly congestion prices) and the minimum value, and denote this quantity as the slot value ratio (SVR). For lack of a third vertical axis, the SVR values should be read from the left slot axis but divided by 10.

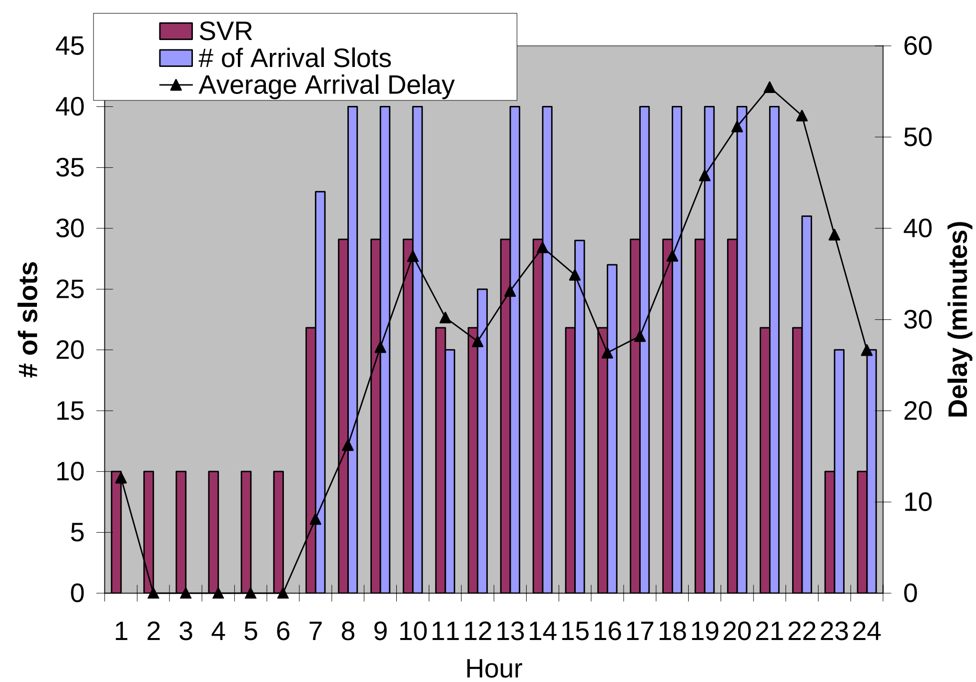

Figure 5. Optimal slot allocations and associated delays.

The target cancellation probability and average delay were set to 5% and 30 minutes, respectively. These values are simply for illustrative purposes; any appropriate values could be used. The resulting numbers of scheduled arrival slots – values of D_t in the above model – are shown in the figure, along with the hourly average queuing delays (from the stochastic model). The values of $D_{\min}$ and $D_{\max}$ were set to 20 and 40 slots, respectively. The upper bound was set based on the VFR arrival capacity at LGA, which is 38, and a 5% probability of cancellation.

It is evident from the above figure that D_t and the slot values (or SVRs) are positively correlated. Hence, more flights are scheduled to arrive during hours with high slots values. The morning peak schedule causes average delay to rise to about 27 minutes per flight during early hours of the day. Due to high slot values later in the evening, demand peaks during 5:00 PM to 9:00 PM, causing queuing delay to go up to 55 minutes per flight during the period 9:00 PM to 10:00 PM. The arrival delay, on average across the whole day, stays below the target of 30 minutes per flight.

We emphasize that this experiment was constructed to illustrate the use of the model and its properties. The parameters used and the model results in no way represent policies of the FAA or policy recommendations on the part of the authors.

Conclusions

We have described a model which, to our knowledge, is the first to compute analytically both the number of cancellations and the size of the stochastic and dynamic queuing delays that one might expect at a congested airport. This model has been conceived and developed as a tool for supporting studies related to the allocation of airport capacity through administrative measures or through market-based mechanisms (such as congestion pricing or slot auctions).

The model we described is "aggregate" and "strategic" in nature and can be used, at the strategic planning level, to capture roughly the impacts that a number of possible congestion management approaches could have on airlines, airports and the traveling public. The setting is one in which only coarse information about the demands and behavior of a number of competing airlines is available. If detailed information about the preferences, choices, and business processes of every individual airline were available, it might be possible to improve the modeling of cancellation probabilities for each specific airline. However, this is unlikely to be the case in practice, since information of this type is closely guarded by the airlines, especially in a competitive environment.

The applications described in this paper were limited to LaGuardia, where it was pointed out that some special circumstances exist that affect modeling choices. Other airports, however, could be studied with essentially the same methodology, after appropriate adjustments. Moreover, it should be obvious from its generality, that this "cancellations-and-delays" model can be highly useful in a wide variety of other contexts.

Acknowledgement

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Keywords

Airspace congestion management, queuing model, network flow model, strategic simulation, delay estimation, cancellation probability.

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