Using Optimization and Queuing Models to Estimate Long-Term Average Flight Delays and Cancellation Rates

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EXTENDED ABSTRACT

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 managing congestion at New York's LaGuardia Airport (LGA). The project was motivated by the expiration on January 1, 2007 of the legislation authorizing the "High Density Rule" (HDR). The HDR provided a mechanism for limiting the number of arrival and departure slots at LGA and for allocating them to airlines. The NEXTOR project considered several alternative approaches to balancing demand and capacity including administrative controls to limit demand, congestion-based landing fees and slot auctions.

Strategic simulations are experiments in which actual decision makers participate in a simulated exercise. Probably the best know examples of such simulations are the "war games" used to test military preparedness. 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.

Classical approaches to estimating delays view the delay experienced by an entity as a random variable that is a function of other random phenomena including arrival and service processes. In the air transportation context, while delay is certainly highly stochastic, the airlines can exercise substantial control over the amount of delay and its distribution among flights by judiciously substituting flights among allocated slots and by canceling key flights. The degree of control exercised by airlines has been improved substantially with the implementation of Collaborative Decision Making (CDM) procedures in the U.S. (see Wambsganss, 1996 and Vossen and Ball, 2006). However, overall system performance should be measured both in terms of flight delays and flight cancellation rates. In fact, research has shown that passenger delays are very substantially impacted by flight cancellation rates so that ignoring these can greatly misrepresent system performance (see Bratu and Barnhart, 2005). For these reasons it is important to estimate both flight delays and cancellation rates. At the same time, it becomes evident that cancellation rates, while motivated by random phenomena, are the result of human control actions.

We now mention some important characteristics of the problem we addressed and the modeling implications.

Long-term averages and capacity scenarios: our ultimate goal was to estimate long-term average flight delays and cancellations rates. As such our model could not assume one set of airport conditions that might occur on a particular day. Rather we employed a set of capacity scenarios. Each scenario specified hourly airport acceptance rates (arrival capacities). Acceptance rates vary with weather conditions. Recent research (Liu et al 2006) has produced such scenarios for several U.S. airports. Our models then produced delay estimates for each scenario, which could be combined to produce long-term averages using the associated scenario probabilities.

Sensitivity to schedule changes: in the strategic simulation as well as in other potential applications, the model must be able to react to airline schedule changes. Such changes might involve the addition or deletion of flights, but also, might involve moving flights to different time periods within a day, e.g. to avoid highly congested periods. To model these manipulations we produced hourly delay and cancellation rates so that an airline's overall values would be calculated based on the airline distribution of flights over the day.

Isolating impact of a single airport: the National Airspace System is highly complex so that delays at one airport can substantially impact delays at another. On the other hand, our objective was to model the impact of schedules and policies at a single airport. By necessity some interaction effects could not be considered and to an extent we had to implicitly make assumptions about the "outside world", i.e. other airports. Moreover, creating and validating models that do in fact isolate a single airport's impact represented a research challenge.

Daily schedules and delays are broken down into values for each of several time periods (in our experiments a time period was 1 hour in length). Arrival capacity is also handled in a similar way. Thus, an arrival capacity scenario is a vector giving a capacity value for each time period. Let q and a be the scenario and airline indexes, respectively and p_q be the scenario probability. D_{ta}^-, D_{ta}^+ are defined to be the inbound and outbound demand (number of scheduled flights), respectively, during time period t for airline a. d_{tq}^-, d_{tq}^+ are the average inbound and outbound delay, respectively, during time period t under scenario q and d_q^-, d_q^+ are the overall average inbound and outbound delays under scenario q. r_{tq} is the cancellation rate during time period t under scenario q. Finally, the ultimate objective of our models is to compute Γ_a^+, Γ_a^-, the average outbound and inbound delay respectively for airline a and ρ_a, the overall cancellation rate for airline a. These are calculated by:

$$\Gamma_a^+ = \sum_q p_q \frac{\sum_t D_{ta}^+ d_{tq}^+}{\sum_t D_{ta}^-}, \; \Gamma_a^- = \sum_q p_q \frac{\sum_t D_{ta}^- d_{tq}^-}{\sum_t D_{ta}^-}, \; \rho_a = \sum_q p_q \frac{\sum_t r_{tq} D_{ta}^+}{D_{ta}^+}.$$

We note that, except in unusual situations, because of conservation of flow requirements, whenever an inbound flight is canceled, a corresponding outbound flight must be canceled. For this reason, we estimate an inbound cancellation rate and assume it applies to both inbound and outbound flights.

The cancellation model estimates the vector $(r_{1q}, r_{2q}, \ldots)$ given for a given capacity scenario q. Similarly, the delay models estimate $(d_{1q}^+, d_{2q}^+, \ldots)$ and $(d_{1q}^-, d_{2q}^-, \ldots)$ for a given q. On a given day under conditions of reduced capacity and congestion, the airlines must take into account a wide range of considerations in developing a cancellation strategy. Some decisions are highly reactive, e.g. canceling a flight, which by necessity would have been delayed several hours, while other decisions are proactive, e.g. canceling a flight early in the day in order to reduce delays on flights later in the day. Since our objective is to estimate average delays over longer periods of time it is not appropriate and, in fact, not possible to take into account specific conditions on a given day. Rather, given a capacity scenario, we develop a network flow model that develops a cancellation profile to achieve certain delay objectives. The parameters of this model are adjusted so that the model's output matches longer-term cancellation and delay statistics. We do not claim that this model actually mimics airline decision-making. However, its objective and overall decision-making strategy is consistent with those of the airlines. For these reasons, the model is able to produce statistically similar results.

In order to estimate arrival delays, we employ the DELAYS queuing model (see Horanjic, 1990 and Malone, 1995). This model has many important features that make it appropriate for this setting. In particular, it allows arrival and service rate parameters to vary by time period and it does not assume equilibrium conditions but rather numerically solves the equations describing an $M(t)/E_k(t)/n$ system. Further, it does not just estimate average delays but provides an entire delay distribution. At the same time, given the complexities of the NAS, it certainly must be considered an approximation of the actual queuing system. We provide an analysis validating this model that factors out delay propagation effects.

One might be tempted to develop a second queuing model to estimate departure delays. However, the biggest component in departure delays is the delay propagation caused by arrival delays, i.e. the equipment and crews used on a late arrival flight are likely to induce a delay on a departing flight(s) using the same resources. It is also the case that reductions in arrival capacity correlate with reductions in departure capacity. Based on this logic, we develop a regression model that estimates the departure delay vector from an arrival delay vector.

We believe this research makes several important contributions. First, it provides a unique integration of modeling components to estimate overall system performance, which includes both average flight delay and cancellation rates. Nearly all existing NAS performance models focus exclusively on delay. Second, to estimate cancellation rates, we develop a network flow model that serves as the basis of a technique for generating statistical estimates. Both the model itself and its use in this context are novel. Validating the use of queuing models for NAS delays is notoriously difficult because of the high degree of complexity and interaction effects. Our validation approach for the use of the DELAYS model is able to factor our delay propagation effects and provide effective results. This represents a third major contribution.

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