Analysis and Modeling of Ground Operations at Hub Airports

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Abstract: Building simple and accurate models of hub airports can considerably help one understand airport dynamics, and may provide quantitative estimates of operational airport improvements. In this paper, three models are proposed to capture the dynamics of busy hub airport operations. Two simple queuing models are introduced to capture the taxi-out and taxi-in processes. An integer programming model aimed at representing airline decision-making attempts to capture the dynamics of the aircraft turnaround process. These models can be applied for predictive purposes. They may also be used to evaluate control strategies for improving overall airport efficiency.

1 Introduction

As the demand for air travel increases, congestion and delays in the air traffic system become more commonplace. Inherent delay uncertainty makes it difficult for airlines and air traffic service providers to manage passengers, fleets and crews. In addition, increased congestion at busy airports results in significant financial and environmental inefficiencies. Accurate information about an aircraft's current and projected position in the system is extremely valuable to airlines and air traffic service providers alike. Many of the recorded delays can be directly or indirectly attributed to airports. Thus, several efforts are underway to improve airport congestion management, throughput and predictability. To achieve the goal of increased predictability and airport efficiency, much research has been undertaken to study both the departure and the arrival processes at busy airports.

All quantitative approaches to predicting and improving airport operations must eventually rely upon mathematical models. Most highly detailed models of airport operations such as SIMMOD, TAAM or the Airport Machine are based on a detailed, physical modeling of the airport operations [1]. These models can be useful to evaluate qualitatively the relative effects of various airport improvements on airport efficiency. However, calibrating and validating them in a formal sense is a very challenging, if not impossible task. As a consequence, these models require very significant efforts and extensive working knowledge of the particular airport under study to provide quantitative information about the effect of improved airport processes.

In reference [2], pilot reports, on-site investigations and statistical analyses of automatically recorded data indicate that runway capacity is the primary limiting constraint in the departure process at busy airports like Boston Logan International airport. For example, substantial congestion was observed at Logan Airport under certain airport configurations, leading to significant environmental and financial inefficiencies. This observation led to the construction of aggregate airport departure models [3], which were used to predict taxi-out times. It was shown in [4] that these models could be thoroughly calibrated and validated, and that they could be used to quantify the effects of holding departing aircraft at their gates during periods of taxiway system congestion.

The airport arrival process has been studied intensively for airborne traffic, especially through the development of airport arrival management tools such as the Center/TRACON[1] Automation System (CTAS), a suite of decision support tools to help the TRACON manage the flow of aircraft arriving at a busy airport. Arrival management tools such as CTAS provide two benefits for congested airports. First, they contribute to increasing airport throughput by achieving efficient runway balancing and regularizing aircraft arrival flows. Second, the powerful model-based trajectory prediction of CTAS enables the accurate prediction of aircraft landing times up to 40 minutes in advance [5,6,7]. These accurate landing time estimates have the potential to benefit airlines substantially by offering them advance information about incoming flights.

In contrast, most studies of the air transportation system do not consider ground operations. In fact, in many models the ground time, which includes all processes and activities from wheels-on to wheels-off, is assumed to be of constant length. This assumption ignores queuing effects arising at airports and it implies that the airlines cannot influence delays and delay propagation while aircraft are on the ground. However, in practice airlines frequently attempt to shorten the ground times of delayed aircraft in order to control the downstream impacts of delays.

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[1] TRACON: Terminal Radar Approach CONtrol

This paper is organized as follows: It first extends the observational base of arrival and departure ground operations from a moderate-size, non-hub airport such as Boston-Logan International Airport to large hub airports such as Dallas/Fort Worth International Airport (DFW), George Bush Intercontinental Airport in Houston, Texas (IAH), and Atlanta Hartsfield International Airport (ATL). Then this paper presents three models designed to capture the dynamics of ground operations at busy hub airports, including an arrival (taxi-in) model, a ground (aircraft-turn) model, and a departure (taxi-out) model. Finally, the paper presents possible applications for the three models currently under development, including (i) a predictive capability for air transportation system monitoring purposes, (ii) a means to evaluate policies aimed at managing airport congestion by queue delay management, and (iii) a means to evaluate the potential economic impacts of airline intervention in the aircraft arrival scheduling process.

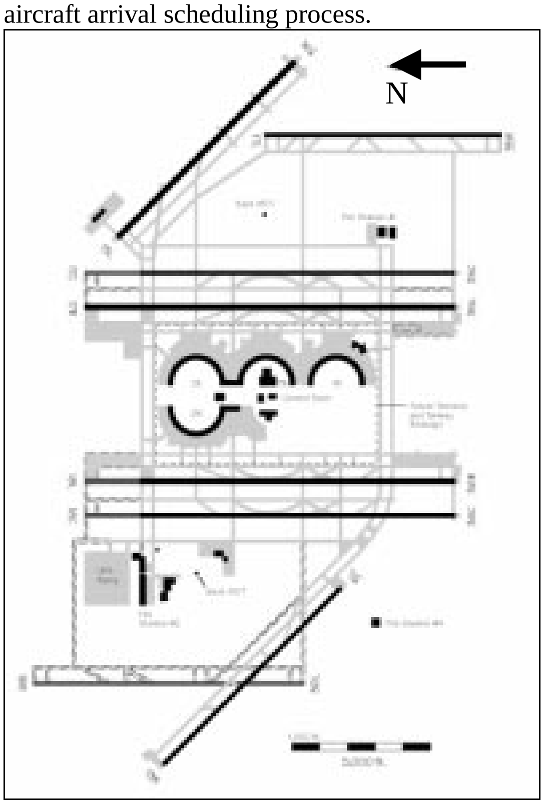

Figure 1: Map of DFW.

2 Available Data

2.1 Airport Layouts

As shown in Figure 1, DFW is oriented in a north/south configuration with east and west sides running almost independent operations [8]. On the west are two parallel runways and one diagonal runway, and on the east side are three parallel runways and one diagonal runway. The parallel runways are spaced such that simultaneous operations can occur. A "south configuration" includes the use of any runways in the set of 18R/L, 13R/L, and 17R/C/L runways. A "north configuration" includes the use of any runways in the set of 31R/L, 36R/L, and 35R/L runways. At any time, several runways are simultaneously available for departure and arrival operations.

ATL had four runways at the time of data collection, oriented in an east/west configuration, as shown in Figure 2 [8]. The four runways consist of two sets of parallel runways: two to the north and two to the south. The runways are spaced such that simultaneous operations can occur. An "east configuration" includes the use of any runways in the set of 8R/L and 9R/L runways. A "west configuration" includes the use of any runways in the set of 26R/L and 27R/L runways. At any time, several runways are simultaneously available for departure and arrival operations.

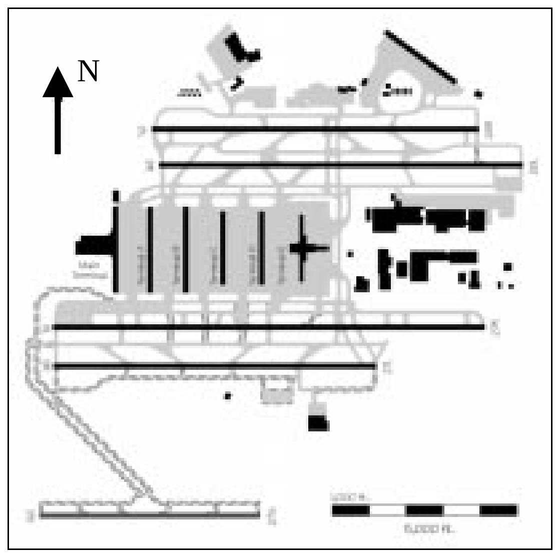

Figure 2: Map of ATL.

IAH has six runways, oriented in an east/west overall orientation, as shown in Figure 3 [8]. The six runways are partitioned as three pairs of parallel runways: two to the north, two to the south and two diagonal runways. The parallel runways are spaced such that simultaneous operations can occur. An "east configuration" includes the use of any runways in the set of 8R/L, 9R/L and 14R/L runways. A "west configuration" includes the use of any runways in the set of 26R/L, 27R/L and 32R/L runways. At any time, several runways are simultaneously available for departure and arrival operations.

2.2 Flight Operations Data

The analyses discussed herein rely on the Airline Service Quality Performance (ASQP) database, which provides information about the jet operations of 10 major airlines: Alaska; American; America West; Continental; Delta; Northwest; Southwest; TWA; United; and US Airways. For most of these airlines' flights, ASQP provides both scheduled and actual pushback, take-off, landing and gate arrival times. Note that because the ASQP database includes jet operations only, it does not provide a complete picture of the activity at each airport. For example, it captures approximately 66% of the operations at Dallas/Fort Worth, with similar percentages at the other airports considered in this paper.

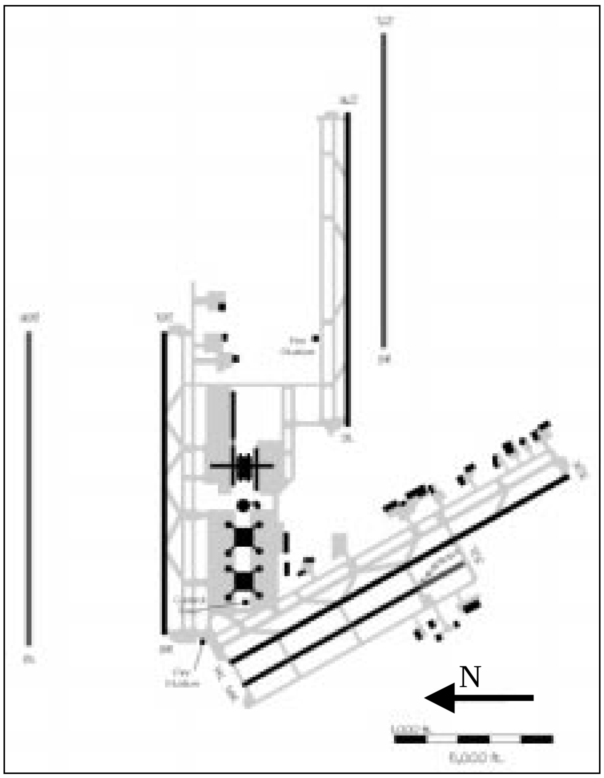

Figure 3: Map of IAH.

The accuracy of the ASQP data has been confirmed via independent observations. Visual observations at Boston-Logan airport confirmed ASQP recorded push-back times [9]. A formal validation of take-off and landing times recorded in the ASQP data was done by cross-checking them against high-resolution, timed radar tracks available at DFW. A threshold location was chosen on the departure path or on the final approach path roughly 5 Nautical miles from the runway threshold, and the time difference between the recorded wheels-off time (available from ASQP) and the time of threshold crossing (obtained by radar track interpolation) was computed and detrended for all jet aircraft that used that particular runway. As may be seen from Fig. 4, the ASQP records closely match estimated take-off and landing times generated from high-resolution, timed radar tracks provided by CTAS at DFW; the ASQP data is accurate to within its one-minute round off error.

It is worth noting that the estimated landing and take-off times from radar tracks do not rely upon ETMS estimates or data.

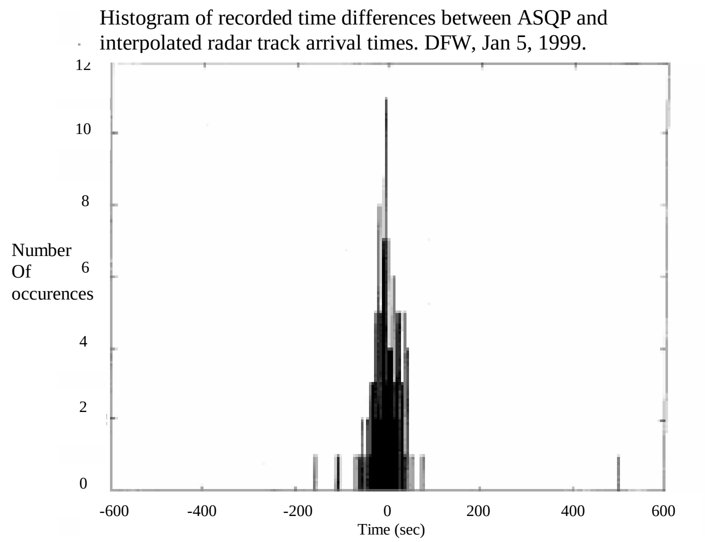

Figure 4: ASQP and radar track agree

2.3 Weather and Airport Configurations

Based on field observations and data analysis at Boston-Logan Airport [10], airport runway configuration is a major determinant of ground operations dynamics. In particular, runway configuration is a major factor to determine airport arrival and departure acceptance rates. Unfortunately, historical runway configuration data are not readily available for the hub airports studied in this paper. However, detailed historical wind and weather data are available from the Consolidated Operations and Delay Analysis System (CODAS) database, which provides airport-specific weather information over 15-minute intervals. The CODAS weather data includes wind speed; wind direction; wind gust; temperature; precipitation; ceiling; and visibility. The data set is remarkably complete. For example, at DFW in 1997, only eight 15-minute intervals are missing from the records, and only 7% of the temperature data are missing, while all of the other data fields are complete.

While weather conditions alone do not fully determine runway configuration (e.g., in the case of Boston Logan Airport, environmental concerns are also a significant influencing factor), the CODAS data may still be used in conjunction with airport layout information to partition the available operations data into distinct *segments*[2]. For this

[2] For this work, a *segment* is defined as a particular combination of runway operability and weather conditions,

paper, we considered CODAS data from 1997 for DFW and from 1998 for IAH and ATL. A summary of the segmentation methodology and results of this segmentation is provided here for the three airports studied. The same segmentation methodology was used for each airport, with changes to accommodate the different runway layouts.

With the help of an experienced jet pilot employed by a major US airline, a set of standards was developed for runway operability and airport capacity under various weather conditions. A runway was considered operable if the crosswind was less than 20 knots and the headwind was positive. Otherwise, the runway was considered inoperable. If the wind data over an interval were incomplete, a conservative approach was used to estimate the runway configuration: if at either end of the interval a runway was considered inoperable, the runway was considered inoperable during the entire interval. Further segmentation was then conducted to include weather factors such as ceiling, visibility and precipitation (including thunderstorm activity), all of which are known to influence airport capacity significantly. Each of these weather factors was assigned a threshold at which it was considered to affect the airport operations. Precipitation was considered to affect operations when there was thunderstorm activity or when precipitation was indicated[3]. Ceiling was considered to affect operations when it dropped below 1000 feet. Visibility was considered to affect operations when it dropped below 3 miles.

The first step in the segmentation process was to estimate the runway configuration for each 15-minute interval using the CODAS winds data. After determining the runway configurations, the number of operations occurring under each of the configurations was tallied. The percentage of operations occurring under each of the determined runway configurations for each of the airports is shown in Figures 5 through 7. Note that the "no runways available" bin includes both times of severely high winds and times of incomplete wind data for which the runway operability was conservatively estimated using the method described above. The second step in the segmentation process was to consider additional weather factors such as ceiling, visibility, temperature, and precipitation. Using the thresholds described above, each of the four weather factors was assessed as to whether it affected airport operations for each 15-minute interval. The number of operations occurring under each of the weather conditions was tallied. The percentage of operations occurring under each of the determined weather conditions for each of the airports is shown in Table 1.

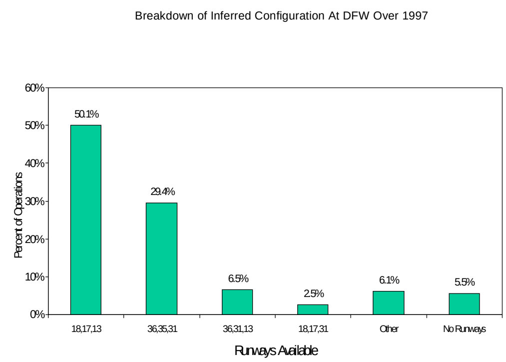

Figure 5: Configuration breakdown for DFW.

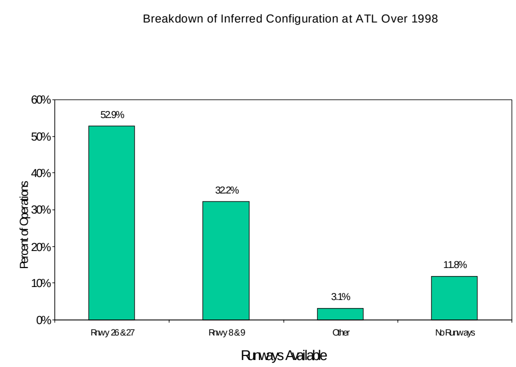

Figure 6: Configuration breakdown for ATL

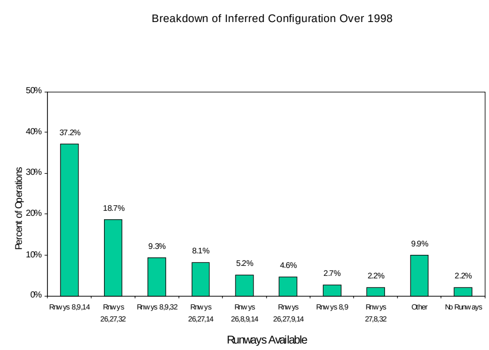

Figure 7: Configuration breakdown for IAH

WEATHER FACTOR	DFW	ATL	IAH
% of ops affected by ceiling	5%	9%	6%
% of ops affected by visibility	3%	8%	6%
% of ops affected by precipitation	3%	4%	4%

Table 1: Influence of weather

independent of actual runway operations or standard operating procedures.

[3] The precipitation entries in the database belong to the set {0,1,T} where 0 indicates no activity, T indicates a thunderstorm and 1 indicates the presence of precipitation.

The final step in the segmentation process was to link the runway configuration for each 15-minute interval to the corresponding weather data to create distinct segments. Even though the number of possible segments is large, operations only occur during a small subset of the possible segments. As might be expected, for the three airports studied the majority of the operations occurred under the segments corresponding to the primary runway orientation of the airport, as defined in Section 2.1. At DFW, the segments corresponding to the north/south configuration represent 80% of the operations. Similarly at ATL and IAH, the segments corresponding to the east/west or north/south configurations represented 85% and 56% of the operations, respectively. Given this result, the possible segments were summarized into six segment groups: the two primary configurations under good weather conditions, the two primary configurations under inclement weather conditions[4], indeterminable configuration and "other". The number of operations occurring in each of these 6 segments for the three airports is shown in Table 1 below.

SEGMENT	DFW		ATL		IAH	
N/E Good	26.6%	#1	24.2%	#1	31.4%	#2
S/W Good	46.4%	#2	48.2%	#2	16.5%	#1
N/E Bad	2.8%	#3	8.0%	#3	5.9%	#4
S/W Bad	3.7%	#4	4.7%	#4	2.3%	#3
Other	15.0%	#5	3.1%	#5	41.7%	#5
Excluded	5.5%	#6	11.8%	#6	2.2%	#6

Table 2: Final results of segmentation analysis by airport.

These results have not been explicitly validated for the three airports because historical runway configuration data is not readily available. However, our results support anecdotal reports that the south configuration is the primary configuration for DFW. Similarly at ATL, the segmentation results above are consistent with the account that the west operation is considered the most efficient, and hence is the preferred configuration. Further, we were able to validate the segmentation results at DFW in an implicit sense using radar track data: Through an analysis of radar-track data from CTAS, the runways used for take-offs and landings were determined, and then compared against the weather-inferred runway configurations. In general, the weather-inferred configurations were the same as the radar-inferred configurations. The orientation of each configuration (north/south) was identical, but the weather-inferred set of runways often varied slightly from the radar-inferred set of runways, probably due to the sensitivity of the weather-inferred configuration to short-term changes in wind speed and direction and weather.

[4] Inclement weather conditions means that either ceiling or visibility was below its defined minimum or precipitation was above its defined maximum. Note that low temperature alone does not qualify as inclement weather for the three airports studied.

3 Models

3.1 Departure Process (Gate Pushback to Takeoff)

3.1.1 Modeling Approach

The general approach taken to modeling the taxi-out process is to treat the system as an input/output system with very simple dynamics. The model is intended to capture the observed statistical behavior of the departure process, rather than replicate the exact physically- and procedurally-constrained dynamics of aircraft motion on the airport surface. This approach has the advantage that particular models can be easily calibrated and validated to describe a wide variety of airports under various traffic and weather conditions, and statistically significant conclusions can be drawn from these models.

3.1.2 Observed Behaviors of the Departure Process

Based on extensive field observations at Boston-Logan Airport [10], and analysis of historical data from BOS, ATL, and DFW, there are several major behaviors of the departure process that the model must capture. The taxi-out time of a particular aircraft (from pushback to takeoff) is primarily determined by the departure congestion at pushback, i.e. the number of departing aircraft that are already on the airport's surface but have not yet taken off. When departure congestion is low, a nominal (or unimpeded) distribution of taxi-out times can be observed for aircraft pushing back from a particular gate. Aircraft are often observed to reach the active runways in a different order from their pushback sequence, indicating that the departure traffic flow up to the runway is relatively unconstrained.

In contrast, once an aircraft reaches the runway, it usually enters a runway queue, and its position in the queue becomes fixed. The airport throughput is primarily limited by this bottleneck effect at the runways [2]. Runway configuration and weather are observed to be the primary factors which determine the behavior of the runway queue, including the maximum runway throughput, and the approach to throughput saturation as a function of rising departure congestion.

3.1.3 Proposed Model Structure

Based on these behaviors, simple queuing structures are proposed to represent the input-output system dynamics. Aircraft enter the system after they have called ready for pushback and have been given pushback clearance by the tower; they leave the system at the time they take off.

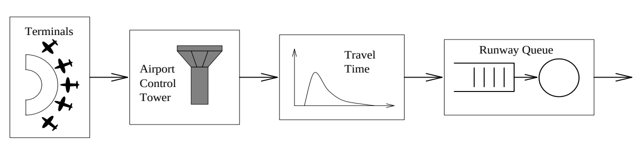

Figure 8: Proposed Queuing Model for the Departure Process

The initial unconstrained phase of departure traffic flow is modeled as a random delay, where each aircraft that pushes back is assigned a stochastic taxi-out time to reach the active runways. The probability distribution of these taxi-out times is taken to be the nominal (unimpeded) taxi-out time observed at low congestion levels. Ideally, to capture the differences in travel time due to different gate locations, each gate would be assigned an individual probability distribution. Unfortunately, historical gate-assignment information is not readily available. However, it has been found that the airline for each flight is a reasonable proxy variable since the gates for a particular airline are often clustered at a particular terminal [11].

Once aircraft complete their nominal taxi-out time, they are assumed to enter the runway queue. This queue is first-come first-served, which captures the bottleneck and sequencing effects observed near the active runways. During each interval of time, a stochastic number of takeoff opportunities is available, and aircraft at the head of the runway queue can exit the system if sufficient opportunities are available. This stochastic behavior is observed under conditions of high departure congestion, when the runway system is almost certainly non-empty. In reference [11], a similar queuing model for the airport departure process was proposed, and extensively calibrated and validated for Boston-Logan Airport using several years of historical runway configuration and traffic data. Our current model uses the same queuing structure but proposes several changes to the runway queue model, and to the calibration and validation techniques.

3.1.4 Calibration Methods

Based on results from [10], a method has been developed to observe the nominal (unimpeded) distribution of taxi-out times. Each departing flight is assigned an index (denoted "N_H") that counts the number of other aircraft which takeoff while that flight is taxiing out on the airport surface. If a particular flight is held on the airport surface after pushback due to downstream restrictions, mechanical problems, bureaucratic delays, or other effects which are unrelated to departure surface congestion, it will tend to be passed on the taxiway by other departing aircraft, and its N_H index will be large. If a particular flight pushes back and encounters substantial queuing delays near the runway, then its N_H index will be large due to the large number of other departing aircraft which takeoff while it waits in the queue. Therefore, flights with a low N_H index are assumed to have experienced little delay while taxiing out to the runway, and the nominal (unimpeded) distribution of taxi-out times is estimated from their taxi-out times. It is worth noting that the N_H index cannot be calculated at the time an aircraft pushes back from the gate, and hence it cannot be used directly in real-time to predict taxi-out time.

The effect of N_H on the observed distribution of taxi-out times is shown below in Figure 9. The plot shows how the observed distribution increases in both mean and variance as a function of increasing values of the N_H index. Similar results are found for ATL and DFW.

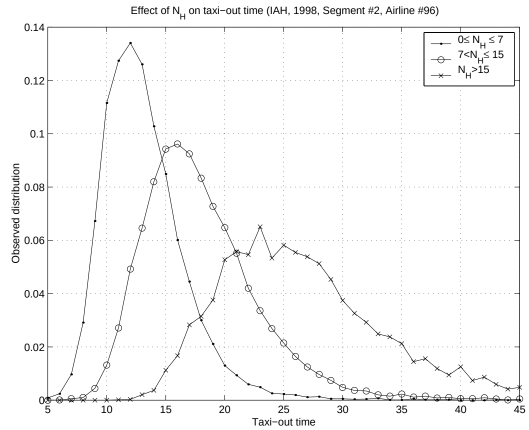

Figure 9: Effect of N_H on taxi-out time distribution at IAH.

Gaussian or log normal distributions are used to approximate the underlying distribution on unimpeded taxi-out time. The stochastic model for the runway queue behavior is based on the observation that, at a fixed level of departure congestion, the distribution of takeoffs over each one-minute interval is well fitted as a Poisson distribution. Further, as the level of departure congestion increases, the rate of the fitted Poisson distribution increases, until a threshold is reached where further increases in departure congestion levels do not result in increased rates. Based on these observations, the runway queue is modeled as providing a stochastic number of takeoff opportunities during each interval of time, where the distribution of the number of opportunities is Poisson with the maximum observed rate.

A type of runway throughput plot was developed to aid in calibrating this model. At each level of departure congestion, a Poisson distribution (with 95% confidence intervals) is fitted to the observed distribution of takeoffs. Then these fitted rates are plotted as a function of the departure congestion level to yield a throughput plot. Additionally, the number of time-intervals at each level of departure congestion is plotted to ensure that sufficient data-points are being used in the fitting process. Several of these plots are shown below for the various airports studied in this paper.

The first pair of plots (Figures 10 and 11) was made using data from ATL during those intervals in 1998 when the airport was operating in its secondary runway orientation. The first plot corresponds to good-weather conditions, and the second plot corresponds to inclement-weather conditions. Note that the distribution of takeoffs is fitted very well as a Poisson distribution over a wide range of departure congestion levels. It is apparent that the throughput in good-weather conditions saturates at a higher level of congestion than the throughput in inclement-weather conditions.

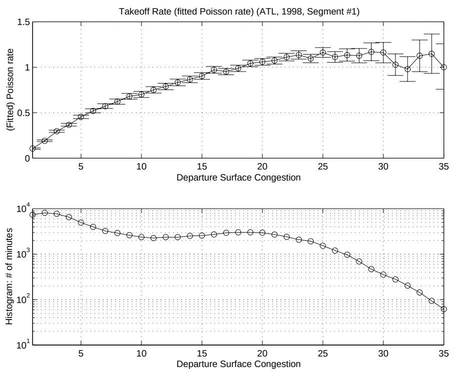

Figure 10: Throughput at ATL during good weather.

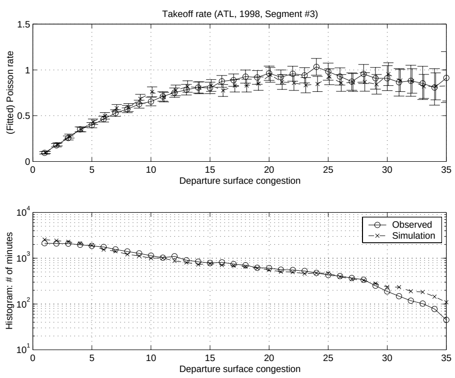

Figure 11: Throughput at ATL during inclement weather.

Overlaid in Fig. 11 are similar statistics collected from the calibrated queuing model of departure operations for that airport segment. According to those statistics, this model matches very well experimental data.

A second pair of plots (Figures 12 and 13) was derived using data from DFW during those intervals in 1997 when the airport was operating in its secondary runway orientation. We observe effects similar to those seen at ATL. However, note that the throughput at DFW during good-weather conditions appears to steadily increase as departure congestion increases; there is no observed saturation effect. In contrast, the throughput during inclement-weather conditions shows a clear saturation effect.

3.1.5 Work in Progress

To date, there are several important observations that have not yet been successfully incorporated into the departure process model. Observations indicate that at some airports, departure taxi-out times tend to increase as arrival congestion increases, where arrival congestion (denoted "N_A") is measured as the number of arriving aircraft that are taxiing in from the runways when a departing aircraft pushes back from the gate.

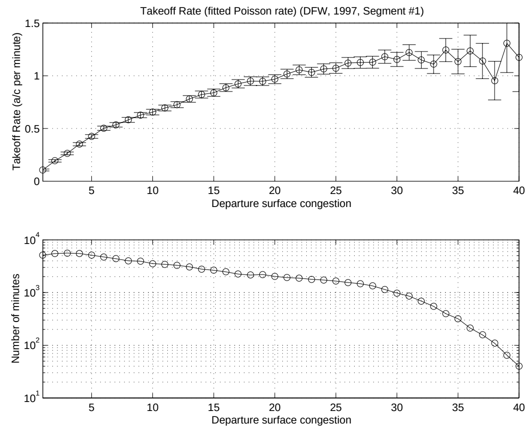

Figure 12: Throughput at DFW during good weather.

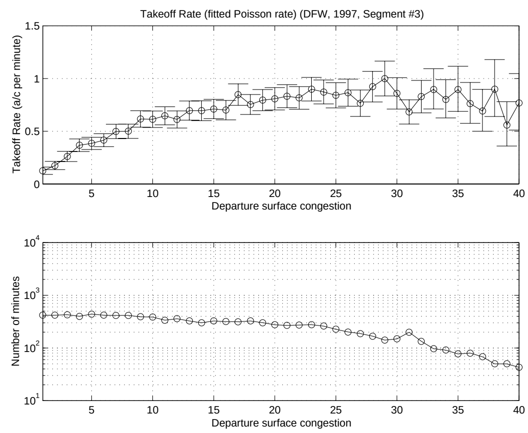

Figure 13: Throughput at DFW during inclement weather.

Figure 14 shows that increasing levels of arrival congestion are clearly related to increasing taxi-out times at ATL. However, the same phenomenon is not readily apparent at DFW (Figure 15). It is not clear if this dependence is the effect of a causal relationship, or if arrival congestion and departure congestion simply have some positive correlation due to the airlines' schedule bunching and block-scheduling at certain hub airports. It is also worth noting that weather breakdown and configuration breakdown are not equivalent; following observations made at Boston Logan Airport, airport capacity may be affected somewhat by weather within a single configuration, as shown in Fig. 16. The effect of prop traffic (which is notably absent from the ASQP database) is currently treated as an additional source of stochastic noise in the system, although in principle the current queuing model can be trivially extended to include prop traffic. Occasionally aircraft experience significantly longer taxi-out times due to downstream restrictions, and work is underway to accommodate these outliers.

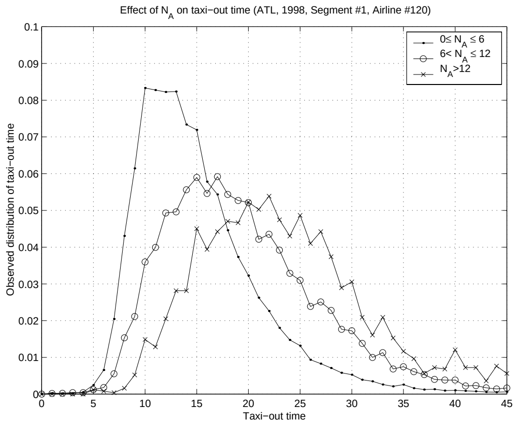

Figure 14: Arrival congestion influences taxi-out times at ATL.

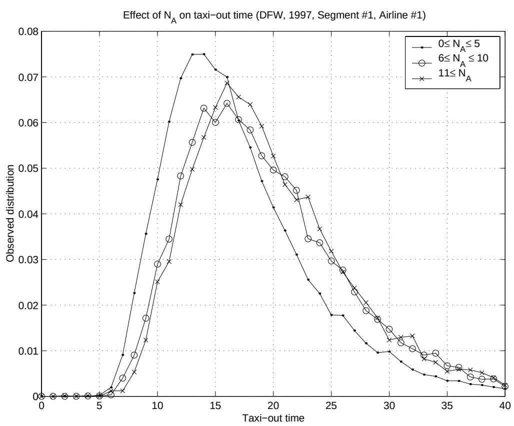

Figure 15: Arrival congestion has limited influence on taxi-out times at DFW.

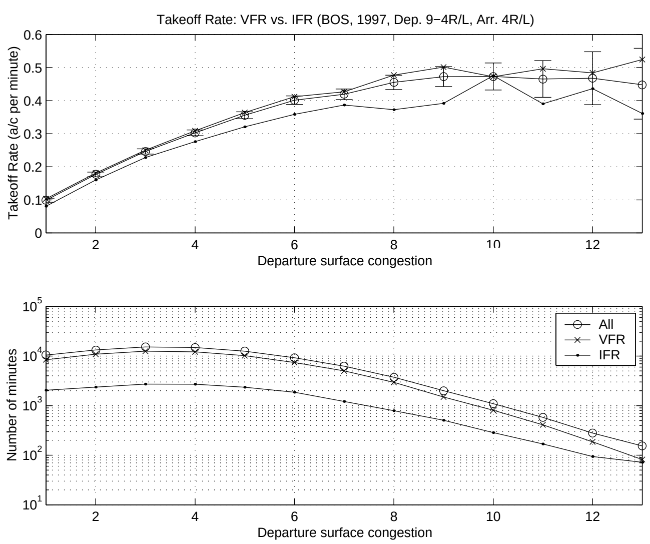

Figure 16: Evolution of throughput by weather, for given configuration at Boston Logan Airport

Finally, it is intuitively obvious that on a very short time-scale there must be some tradeoff between landings and takeoffs on the same runway. This tradeoff is currently treated as an additional source of stochastic noise in the runway behavior, but work is currently in progress to explicitly model this effect in the behavior of the runway queue.

3.2 Arrival Process (Landing to Gate Arrival)

Data analysis at BOS, DFW, and ATL indicate a somewhat surprising result: The statistical behavior of arrival operations can be captured using the same general input/output queuing structures and calibration/validation techniques which are currently used to statistically model the departure process. A diagram of the proposed arrival model is shown below (Figure 17):

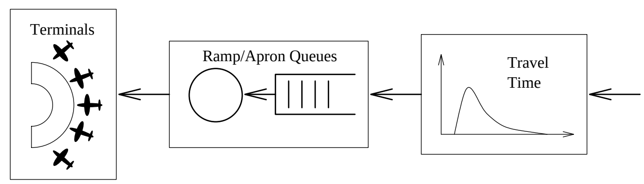

Figure 17: Proposed Queuing Model for the Arrival Process

At first this result is somewhat unappealing, since the structure of the departure model has been explicitly motivated by a specific set of field observations and data-analysis results, and it is not apparent that these observations and behaviors immediately generalize to the arrival process. However, it is possible to view the departure process model in a more general framework. The departure process model is intended to capture a relatively unconstrained period when aircraft are taxiing out unimpeded to the runway queues, followed by a period that is dominated by bottleneck effects near the runway queues. The arrival process follows roughly the same pattern, where aircraft initially taxi towards the gates, and then slow down and queue up near the gates. This effect is especially apparent in airports with physical bottlenecks near certain terminals, such as the corridor-type terminals at ATL and the “Horseshoe” at Boston-Logan Airport.

Nominal distributions of taxi-in times were obtained using the same method used to obtain nominal distributions of taxi-out times. For the arrival process, the N_H index is defined as the number of arriving aircraft that reach the gates while a particular flight is taxiing in from the runways. There are some interesting observations to be made here. Representative distributions of taxi-in time at IAH and DFW are shown in Figures 18 and 19. Note that as N_H increases, the distributions of taxi-in times do not appear to significantly change shape or width at DFW, but are simply shifted to the right. This effect may indicate that the stochastic component of an aircraft’s taxi-in time is approximately *independent* of the arrival congestion, and hence that taxi-in times may have a much higher level of predictability than taxi-out times. Further field observations are necessary to confirm this hypothesis.

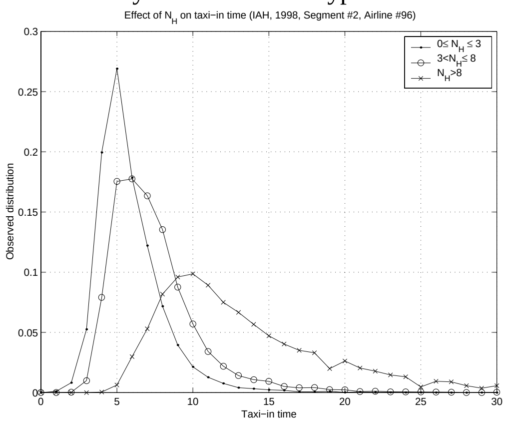

Figure 18: Effect of N_H on taxi-in time at IAH.

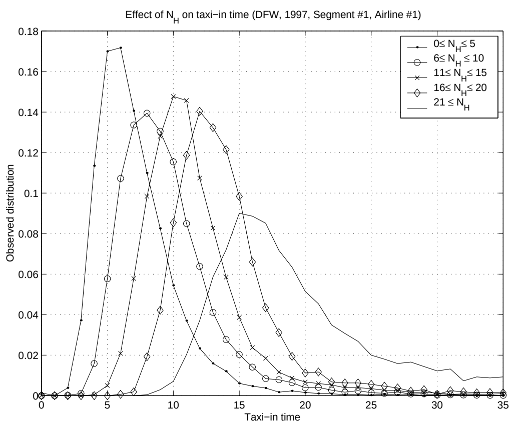

Figure 19: Effect of N_H on taxi-in time at DFW.

Gate throughput curves are also shown. The gate throughput curves for all three airports are quite similar in character. As might be expected, gate throughput appears unaffected by inclement weather conditions at all of the airports studied (see Figures 20 to 23). One interesting observation is that the gate throughput can saturate, similar to the saturation effect in the departure process.

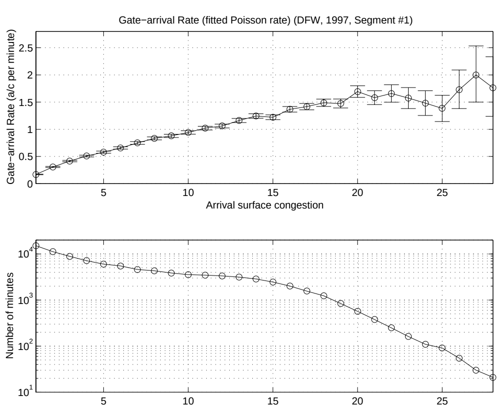

Figure 20: Gate throughput at DFW (good weather).

These observations indicate that gate throughput saturation may be an effect of very high traffic loads, rather than a degradation of the system performance. Again, figure 22 shows statistics obtained for a calibrated arrival model of ATL. Again this model performs quite well with respect to the experimental data.

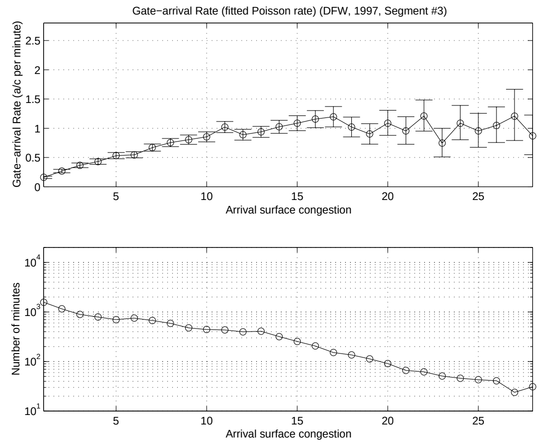

Figure 21: Gate throughput at DFW (inclement weather).

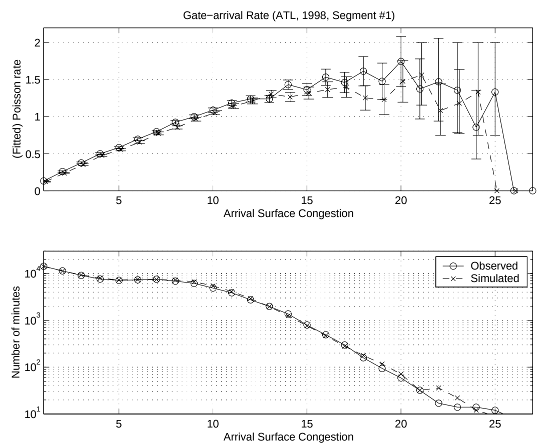

Figure 22: Gate throughput at ATL and calibrated model (secondary runway orientation).

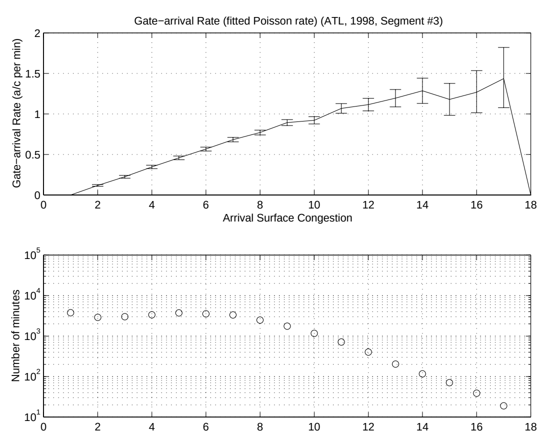

Figure 23: Gate throughput at ATL (secondary runway orientation, bad weather).

3.3 Ground Operations (Gate Arrival to Gate Pushback)

3.3.1 Modeling Approach

The ground operations model is an optimization model designed to simulate airline operational decisions about aircraft pushback times under resource constraints. The ground operations model considers the departure schedule, aircraft-gate compatibility, gate availability and ground crew resource availability in determining pushback times that minimize passenger delay given arrival at gate times. As a result, the model can measure how an airline can reduce delays and delay propagation on the ground. This section includes a description of the ground operations model and results to date from IAH, the only airport for which sufficient ground operations data was available.

3.3.2 Observed Behavior of the Ground Operations

There are many factors contributing to departure delays. This includes arrival delay. To illustrate this, the difference between arrival delay and departure delay was computed. This difference will be referred as delay flow-through. The distribution of delay flow-through for DFW, ATL and IAH is shown in Figures 24-26. Notice that these distributions appear Gaussian, with means greater than zero. In fact, the mean delay flow-through for each airport is positive and the 95% confidence interval of the mean delay flow-through is strictly positive. This positive mean delay flow-through indicates that the arrival delay was somehow reduced while the aircraft was on the ground.

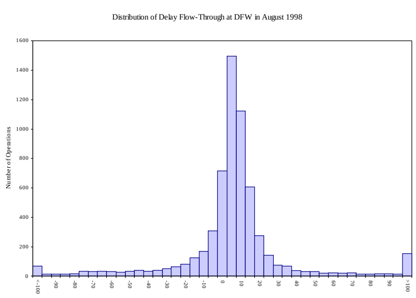

Figure 24: Distribution of flow-through at DFW.

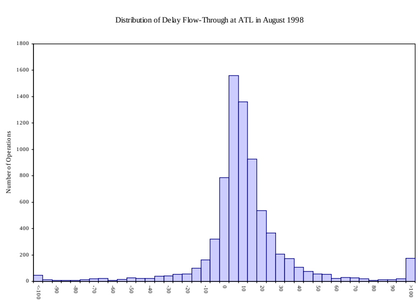

Figure 25: Distribution of flow-through at ATL.

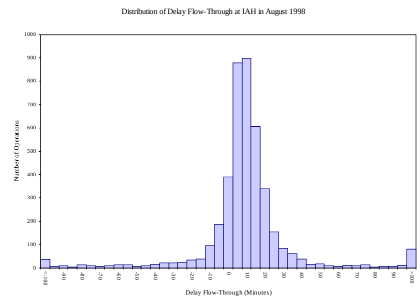

Figure 26: Distribution of flow-through at IAH.

There are two potential explanations for this observation. First, the "slack" in the arrival and departure schedule may have absorbed the arrival delay. For example, assume an aircraft is scheduled to arrive at 10:00 and depart at 10:40 and that the scheduled minimum turn time for the aircraft is 30 minutes. In this case, there are ten minutes of slack built into the schedule. Therefore, the aircraft can arrive up to ten minutes late without affecting the departure time. Second, the airline may have prepared the aircraft for departure ahead of schedule. Continuing with the same example, if the aircraft arrived 20 minutes late, but departed on time, the airline turned the aircraft in 20 minutes, 10 minutes under the scheduled minimum turn time. In this case, the airline reduced the turn time of the aircraft.

To understand the extent to which the airline is able to reduce the turn time of the aircraft in order to reduce delays, we identify aircraft with departure delay greater than 10 minutes and with arrival delay greater than departure delay. For these aircraft, the histogram of the actual turn time minus the minimum scheduled turn time was plotted. The scheduled minimum turn time is the turn time assumed by the airline in the scheduling process. This plot is shown in Figure 27 below for one airline at one of the hubs. Data for other airlines was not accessible. The confidence interval for the mean of the distribution is negative, indicating that the airlines tend to prioritize late arrivals on the ground to reduce the corresponding departure delay.

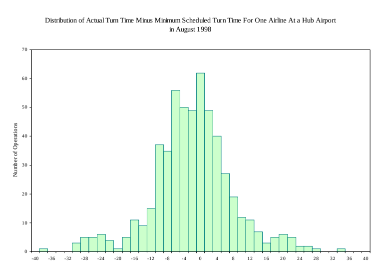

Figure 27: The mean of the distribution of the difference in actual turn time from the scheduled minimum turn time is negative, indicating that airlines prioritize the turning of delayed arrivals.

3.3.3 Model Structure

As discussed above, an airline can reduce departure delay by reducing turn time. However, the results do not indicate exactly *how* an airline achieves the turn time reduction. One of the biggest challenges in modeling ground operations is determining which resources and activities to include in the model. The turn process involves numerous distinct sets of crews conducting distinct activities, including baggage unloading and loading, catering, cleaning, maintenance, passenger deplaning and boarding, and so forth. During visits to airline ground operations centers, key airline personnel indicated that the baggage handling process could be one bottleneck in the turn process. Therefore, we decided to include baggage handler constraints in the ground operations model. The extent to which these constraints explain the variability in the actual turn process is discussed later.

During visits made to airline ground operations, airlines made last-minute decisions to hold departing aircraft to accommodate connecting passengers from a delayed arrival flight. In order to incorporate this decision process into the model, the ground operations model explicitly considers passenger flows. If a passenger connection is missed, the total delay to that passenger, which is the time until the next departure to the same destination, is included in the objective function. This means that the ground operations model determines the trade-off of delaying an aircraft to allow for passenger connections and re-routing passengers who miss connecting flights.

Even after carefully deciding which factors to consider, some simplifying assumptions need to be made in order to maintain the tractability of the problem. First, baggage handlers are assigned to aircraft irrespective of their previous aircraft assignments. This assumption means a baggage handler can be assigned to a different aircraft in every time unit. At most hub airports, however, baggage handlers are assigned in *teams* to a particular aircraft for unloading and loading. Therefore, the resulting assignment of baggage handlers may not map to a feasible assignment of baggage handler *teams*.

Second, the ground operations model is a deterministic model, meaning there is no stochasticity incorporated in its design. In particular, the taxi-in times of the aircraft are assumed constant. As discussed above and seen in Figures 18 and 19, this is not true in practice. The extent to which this assumption affects the model remains to be addressed.

Finally, the objective function is measured in passenger-minutes, which is not a metric directly linked to the airline's cost structure. The translation of this metric to dollars is difficult. However, the metric does link both operational efficiency and the passenger experience, both of which have an effect on the profitability of the airline. Some sensitivity analyses with respect to the objective function are discussed in [12].

The specifics behind the formulation of the integer programming model are not within the scope of the paper; interested readers can refer to [12]. The run time of the ground operations model has shown to be acceptable. Problems including about 80 aircraft and covering a 3-hour time horizon solve in about 1 minute. A detailed description of problem size and run time is included in [12].

3.3.4 Model Calibration and Validation

To determine whether the ground operations model is effective in predicting departure time, its pushback time estimates were compared to those from a simpler, "naïve" model. The naïve model is designed with a constant turn time, based on the minimum scheduled turn time. The basic difference between the models, therefore, is that the ground operations model provides more flexibility and considers ground crew resources and passenger flows in determining departure time.

Since the departure times of the aircraft in a particular scenario are interdependent in the ground operations model (the aircraft share finite resources), multiple independent scenarios were considered in order to compare the two models. The metric considered is departure error, defined as the model's prediction of departure time minus the actual departure time. For each scenario and for each model, the average departure error and the mean-squared departure error were calculated, with the results depicted in Table 3 below. The data included in the analysis is for twelve days in January, 1998 from 16:00 to 19:15.

Notice that the mean-squared departure errors for the two models are significantly different; the ground operations model errors are generally significantly smaller than the naïve model's errors. In fact, a Wilcoxon signed rank test confirms that the MSE values for the model are less than those for the naïve model with a significance level of 0.2%. This implies that the additional factors considered in the ground operations model are influencing the turn process and are improving the departure time predictions. However, the confidence interval of the average departure delay for the ground operations model does not cover zero. In fact, the confidence interval contains only negative numbers. This means the ground operation model's departure time estimates tend to be earlier than the actual departure time, implying there is some bias in the predictions.

Scenario	Ground Operations Model Departure Error		Naïve Model Departure Error	
	MSE	**Avg**	**MSE**	**Avg**
1	168.66	-0.33	882.21	6.28
2	46.95	-2.29	113.31	0.98
3	46.00	-0.08	107.54	3.74
4	33.04	-1.71	157.02	3.95
5	697.38	-5.27	1,347.09	-3.42
6	563.72	-9.08	1,160.26	-5.86
7	288.54	-3.73	646.04	1.88
8	12.67	-0.67	53.27	1.78
9	16.78	1.07	396.37	8.22
10	122.09	-5.00	382.53	2.98
11	572.92	-7.81	2,409.85	0.69
12	113.02	-4.47	1,757.24	6.07
Average	223.48	-3.28	784.39	2.28
Std. Error	248.32	3.17	752.20	3.98
Lower Bound	82.98	-5.08	358.81	0.02
Upper Bound	363.98	-1.48	1,209.98	4.53

Table 3: The ground operations model produces more accurate departure time estimates than the naïve model, however, the errors do not cover zero, indicating bias in the ground operations model.

To better understand this bias, the distributions of the actual departure delay and the delay predicted by the ground operations model were plotted. This aggregated analysis is necessary because the passenger connection data used in the ground operations model is simulated rather than observed data, meaning the departure time decisions made for a particular aircraft are likely to deviate from actual. However, we would expect the delay decisions to be similar over the entire *set* of aircraft. The distributions for the actual delay and the ground operations model delay are shown in Figure 28 below.

It is important to note that the data set used to generate Figure 28 excludes aircraft for which the difference between actual departure delay and actual arrival delay exceeds 40 minutes. These data points were excluded because delays of that magnitude (greater than 40 minutes) are unlikely to be caused by ground crew resource issues, gate availability or passenger connections. Therefore, some factor(s) external to the ground operations model influenced the departure time. Despite the omission of these identified data points, 5% of departures experienced delays exceeded 40 minutes, while the ground operations model predicted only 2% of departures would incur such delays. However, these excessive actual delays are still likely attributable to factors external to the ground operations model. For example, mechanical problems, ground delay programs and delayed cockpit crews can all lead to delays of 20 minutes or more. If an aircraft is already delayed 20-30 minutes, the departure delay exceeds 40 minutes but is still included in the model.

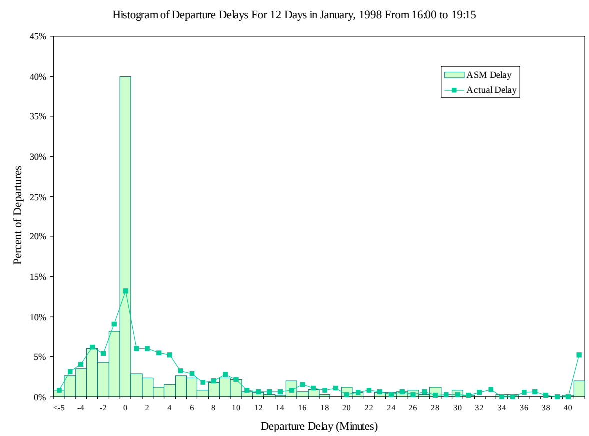

Figure 28: The number of aircraft with predicted delays of 1-4 minutes is far fewer than the number of aircraft actually incurring 1-4 minutes of delay. Further, the number of aircraft with predicted on-time departures far exceeds the actual number of on-time departures.

The major difference in the distributions exists at departure delays of 1-4 minutes. The ground operations model assigns on-time departures to aircraft that were actually delayed 1-4 minutes. The departure process is an extremely complex process involving the synchronization of many resources and sub-processes. Before an aircraft is ready for departure the passengers must deplane the arrival and board the departure, baggage handlers must unload and load the baggage, caterers and cleaning crews must remove rubbish and replenish food and beverage supplies, the aircraft must be checked for flight safety and refueled, the cabin and cockpit crews must arrive and prepare for departure, and so forth. Variability exists in each of these sub-processes. A delay of a few minutes could be caused by numerous factors external to the ground operations model. Recent improvements in the computational performance of the model formulated so far will enable inclusion of some of these factors.

It could be possible to adjust the parameters of the ground operations model to reduce the differences in the results. However, optimizing the parameters, meaning setting the parameters to yield departure time predictions close to actual departure times, is an extremely difficult challenge. The model is sufficiently complicated that it's impossible to determine *a priori* how the parameter changes will affect the solution. Further, and more importantly, it is difficult to identify an optimal parameter setting. It is unknown how much of the deviation from actual departure times is attributable to the use of sub-optimal parameters and how much is attributable to including insufficient information about the ground operations process in the model. This is a fundamental and new research problem encountered in many other types of operations (e.g. military operations) and is currently being addressed.

4 Applications

The three models discussed in this paper have or are being applied to current issues in the air transportation system. This section describes three such applications. First, the models can be integrated to improve predictions of aircraft movement times on the ground. Second, the departure model can be used to evaluate the impact of congestion control on the airport surface. And finally, a semi-integrated arrival and ground operations model is being used to quantify the benefits of procedural changes and decision support tool enhancements.

4.1 Prediction

One immediate potential application for the three models developed for airport operations is to create extend existing predictive capabilities to factor in delays due to airport operations.

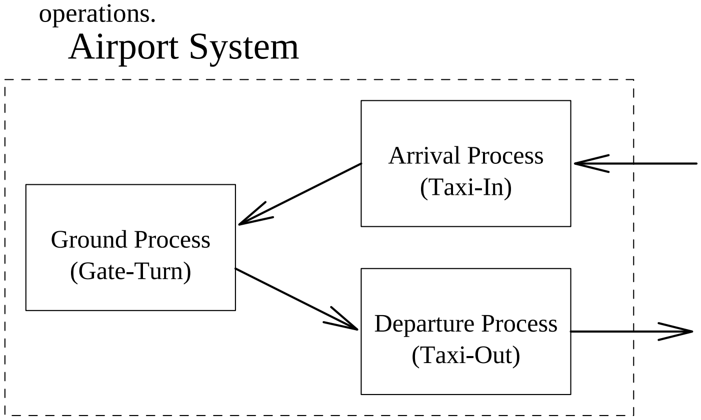

Figure 29: Developing an integrated ground-operations model.

The purpose of such predictive capabilities is to predict anticipated congestion periods better and so that appropriate measures may be taken. The necessary elements for building such a system include the ability to incorporate new information as it becomes available (e.g. knowledge of a pushback request or knowledge of a take off), and the ability to propagate the evolution of the airport system into the future. Conceptually, building such a predictive delay capability is not new; for example Shumsky in his thesis presents departure delay prediction algorithms [3]. The value of such a tool depends upon the quality of the models used. It also is fundamentally limited by the amount of stochastic noise present in the system, which is important in the framework of this paper. As a consequence, planned delay predictive capabilities relying upon the presented models as well as other empirical models [13] will necessarily be probabilistic and will include mean values as well as standard deviations. Building such a tool for most major US airports is the object of current research and development efforts.

4.2 Departure Congestion Control via Gate-Holding Queues

In [4,11,14], a simple control strategy was proposed and investigated to control departure congestion and runway queuing. It is apparent from the departure throughput plots that the runway system has a finite capacity. Based on this observation, it was proposed that departing flights could be held at the gate if the departure surface congestion exceeded some control threshold (denoted "N_C"); the held flights would be immediately given pushback clearance when the departure surface congestion dropped to an acceptable level. This control approach is formally identical to the window flow control mechanism used in packet switched data networks such as TCP/IP networks [15]. This control scheme was shown to effectively trade runway queuing delays for gate-hold delays at Boston Logan Airport. This tradeoff was deemed worthwhile because gate-hold delays are relatively inexpensive in both financial and environmental costs, since the aircraft engines are not running. Further investigation indicated that even strict adherence to this control scheme would cause only a small increase in the occurrence of gate shortages, and would not substantially increase total delays.

A similar departure throughput saturation effect can be seen at the three airports studied in this paper. The effect of the control scheme proposed above was investigated for ATL during segment #3 (secondary runway orientation during inclement weather). Monte Carlo simulations were conducted to simulate the behavior of the proposed departure process queuing model, with the addition of a gate-holding queue whose behavior was controlled by the control threshold N_C and the departure surface congestion. Calibrated distributions of taxi-out times and runway throughput were used to simulate the taxi-out process. The system input was taken to be the sequence of actual push backs recorded in the ASQP database.

The tradeoffs between runway queuing, gate-hold queuing, and total queuing delay are shown below in Figure 30. Note that the simulation results suggest that, at least in the case of ATL under the specified conditions, it may be possible to directly reduce runway queuing by 40% without increasing total queuing delay, and further reductions in runway queuing are possible at the expense of increased total delay. This is a significant number, which confirms earlier estimates for that airport [16]. The percentage of flights that are held at the gate for any length of time is indicated in Figure 31. While the results offer strong evidence of significant potential environmental savings, more in-depth investigation is required to determine whether such a control scheme will cause gate shortages or affect the airlines inequitably.

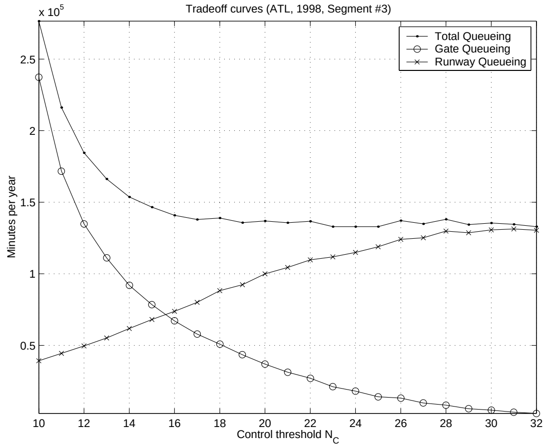

Figure 30: Effect of window control scheme on delay distribution

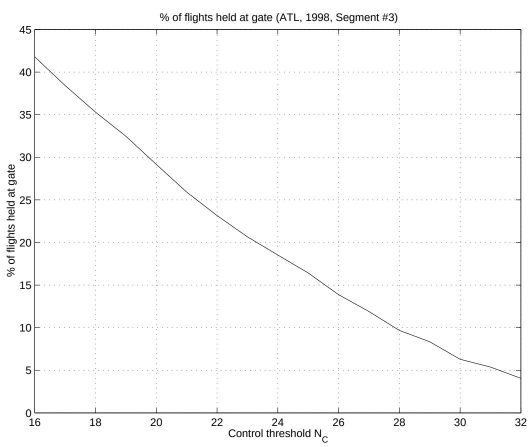

Figure 31: Percentage of flights held at gate.

4.3 Benefits of Alternate Procedures and Improved Decision Support Tools

As noted in the introduction and shown in Figure 32, CTAS produces more accurate arrival time estimates than the airlines currently use to manage their ground operations [3]. The improved accuracy of the arrival time estimates could translate to more efficient use of ground resources. Furthermore, procedural changes combined with new or modified decision support tools could take airline sequence preferences into account when merging arriving aircraft. Therefore, an airline could potentially influence the order in which its arriving traffic landed.

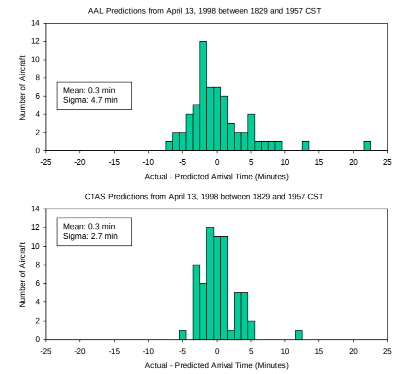

Figure 32: Arrival management tools such as CTAS provides more accurate arrival time estimates at Hub Airports than airlines currently uses to manage their ground operations

To measure the potential benefits of sharing improved arrival time estimates with the airlines and of incorporating airline preferences in the sequence, an integrated arrival and ground operations model is necessary. This integrated model would determine the times of landing, arrival at gate and pushback from gate in order to minimize delays under resource constraints. Ideally, the model would integrate the model structures of the arrival model and ground operations model discussed above. In effect, a queuing model would determine the taxi-in and gate arrival times, while the optimization model would determine each aircraft's movement times including landing, arrival at gate, and pushback from gate. However, the implementation of this is not feasible at this point. The queuing model requires as input the congestion levels of arriving aircraft, meaning the landing times would have to be given. The optimization model, on the other hand, solves for landing, arrival at gate and push back times, given taxi-in time as an input. It is impossible to solve these problems simultaneously. A heuristic approach wherein the models are solved iteratively until they converge on an optimal solution is under development.

For now, we have designed the Airline Sequencing Model (ASM), an optimization model based on the aircraft turn model presented earlier, that considers departure schedule, physical gate resource and ground crew resource constraints in determining an arrival sequence that minimizes passenger delay. In this model, the taxi-in time is assumed to be constant. All constraints considered in the ground operations model discussed in the previous section are included in ASM. A number of additional constraints are included in ASM to restrict the landing and arrival at gate times. First, the model prevents an aircraft from arriving at the gate until it has landed and taxied to the gate. Another important consideration in the model is airline fairness, meaning ASM guarantees that an airline does not improve its operational performance at the expense of another airline's. Fixing the airline's landing times in the model enforces airline fairness; an airline is allowed to shuffle aircraft landing times only within its set of input landing times. Finally, ASM considers gate compatibility and availability. An arriving aircraft can only come to the gates if a gate compatible with its aircraft type is available. Further details of this model and the results from the analysis are included in [12].

It is also important to note that ASM can eventually be used by an airline to manage its arriving aircraft. Assuming that new procedures incorporated the capability for preferential arrival sequencing, an airline could use ASM to determine its optimal sequence. Since ASM solutions are generated quickly [12], its solutions can be incorporated into the models currently used by the airlines to help manage gate and ground crew resources.

5 Conclusion

This paper has considered modeling operations at busy hub airports. Models of aircraft arrival, turn-around and departure operations have been proposed that account for the dominant airport dynamics at each stage. These models have been calibrated. It was shown how these models can be concatenated to build an airport congestion prediction capability, and how these models can be used to evaluate some improvements in airport operations.

6 Acknowledgements

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