

# Queuing Model for Taxi-Out Time Estimation

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## Abstract

Flights incur a large percentage of their delays on the ground during the departure process between their scheduled departure from the gate and takeoff. Because of the large uncertainties associated with them, these delays are difficult to predict and account for, hindering the ability to effectively manage the Air Traffic Control (ATC) system. This paper presents an effort to improve the accuracy of estimating the taxi-out time, which is the duration between pushback and takeoff. The method was to identify the main factors that affect the taxi-out time and build an estimation model that takes the most important ones into account. An analysis conducted at Boston Logan International Airport identified the runway configuration, the airline/terminal, the downstream restrictions and the takeoff queue size as the main causal factors that affect the taxi-out time. Of these factors the takeoff queue size was the most important one, where the queue size that an aircraft experienced was measured as the number of takeoffs that took place between its pushback time and its takeoff time. Consequently, a queuing model was built to estimate the taxi-out time at Logan Airport based on queue size estimation. For each aircraft, the queuing model assumes knowledge of the number of departure aircraft present on the airport surface at its pushback time and estimates its takeoff queue size by predicting the amount of passing that it may experience on the airport surface during its taxi out. The prediction performance of the queuing model was compared at Logan Airport to a running average model, which represents the baseline used currently in the Enhanced Traffic Management System (ETMS). The running average model uses a fourteen-day average as the estimate of the taxi-out time. The queuing model improved the mean absolute error in the taxi-out time estimation by approximately twenty percent and the accuracy rate by approximately ten percent, over the fourteen-day running average model.

## List of symbols and acronyms

$t_{off}$	Takeoff time
$t_{out}$	Pushback time
$T$	Taxi-out time ( $t_{off} - t_{out}$ )
$N$	Number of departure aircraft present on the airport surface at the pushback time of a particular aircraft
$Q$	Takeoff queue experienced by an aircraft
$N^P$	Number of departure aircraft passed by a particular aircraft
$N_P$	Number of aircraft that passed a particular aircraft
NAS	National Airspace System

CDM	Collaborative Decision Making
SMA	Surface Movement Advisor
DP	Departure Planner
TARMAC	Taxi And Ramp Management And Control
GDP	Ground Delay Program
ETMS	Enhanced Traffic Management System
ASQP	Airline Service Quality Performance
ACARS	Air Carrier Automated Reporting System
PRAS	Preferential Runway Advisory System
GS	Ground Stop
EDCT	Expected Departure Clearance Time
DSP	Departure Sequencing Program
MIT	Miles in Trail

## Introduction

In the past few decades, air traffic has increased dramatically while airport capacity has not kept pace with the increased demand. This demand-capacity mismatch has resulted in significant delays. In order to mitigate these delays, more efficient management of air traffic and optimal allocation of the scarce resources of the National Airspace System (NAS) and of the major congested airports are needed. A number of efforts attempt to achieve these goals at the strategic and tactical levels. At the strategic level, flow management tools such as Collaborative Decision Making (CDM) attempt to balance the demand for landing and takeoff slots at major congested airports and the demand for travel through congested airspace sectors with the available capacity (Wambsganss 1997). At the tactical level, tools such as the Surface Movement Advisor<sup>1</sup> (SMA) (Lawson 1998), the Departure Planner (DP) (Anagnostakis et al 2000), and the Taxi And Ramp Management And Control<sup>2</sup> (TARMAC) (Böhme 1994) attempt to allocate airport resources more efficiently within capacity and demand constraints.

One of the main requirements for these improvement efforts is the accurate prediction of aircraft trajectories from gate to gate. The taxi-out segment of the aircraft gate-to-gate trajectory, between pushback from the gate and takeoff, is a great source of uncertainty within the gate-to-gate prediction<sup>3</sup>. This paper presents an effort to improve the accuracy of estimating the taxi-out time. Better taxi-out time prediction will result in better prediction of takeoff times, which in turn should improve the prediction of arrival times at destination airports. The more accurate prediction of departure and arrival demand will assist flow management tools, such as the CDM Ground Delay Program (GDP), at the strategic level. At the tactical level, improved prediction of takeoff times will assist departure planning tools, such as SMA, in managing the airport resources, particularly the runway system.

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<sup>1</sup> A joint Federal Aviation Administration (FAA) and National Aeronautics and Space Administration (NASA) project to help current airport facilities operate more efficiently.

<sup>2</sup> Taxi assistance and guidance system of the German aerospace research center (DLR).

<sup>3</sup> The taxi-out time between pushback and takeoff has more variability when compared to the en-route time between takeoff and landing. For the sample of flights analyzed in this paper, the taxi-out time had a standard deviation of about 11 minutes relative to a mean of about 19 minutes, while the en-route time had a standard deviation of also 11 minutes but relative to a mean on the order of hours.

Existing models for taxi-out time estimation include airline models, which are proprietary, and the Enhanced Traffic Management System (ETMS) model developed at the Volpe Center (ETMS 2000). The ETMS model estimates the Ground Transit Time between the pushback time (scheduled or updated by the airlines) and the takeoff time (measured when the aircraft is captured by the radar tracking system). The ETMS model uses a running average over the past 14 days for reported flights (flights that filed a flight plan). For non-reported flights, the model produces an estimate based on three factors: the day of the week, the time of the day and the duration of the flight. Main factors that may cause delays, such as weather and runway configuration, are not taken into consideration.

Efforts in the research literature that addressed the taxi-out time estimation problem are scarce. Most existing airport system models represent the airport at an aggregate level in terms of landing and takeoff rate capacities (Gilbo 1993) and simple queuing models (Shumsky 1995, Herbert 1997, Pujet 1999, Andersson 2000, Andretta 2000). Shumsky's linear regression model is a notable example that attempted to predict the taxi-out time (Shumsky 1995). Shumsky used airline, departure runway and departure demand as explanatory factors for the taxi-out time. He compared two different measurements of the demand factor: the number of pushbacks scheduled in a time window around the pushback time of an aircraft, and the queue size at the pushback time (measured as the number of departure aircraft present on the airport surface at pushback time). The predictions using the queue size were superior to the predictions using the scheduled pushbacks. The queuing model assumed knowledge of the actual number of pushbacks or required a flow model that estimates the queue size based on knowledge or prediction of the system's capacity at the time. Shumsky compared static and dynamic linear models for taxi-out time estimation and found that the dynamic model (which updated the prediction based on new observations) were beneficial only in the short time horizon. For predictions in a time horizon of an hour or more the static model performed as well as the dynamic model.

In the effort described in this paper, an analysis (described in the second section) was conducted at Logan Airport in order to identify the main causal factors that affect the taxi-out time. The main causal factors identified were the runway configuration, the airline/terminal, the downstream restrictions (which reflect mainly the weather factor) and the departure demand factor measured by the takeoff queue size. Of these factors, the takeoff queue size correlated best with the taxi-out time, especially when the queue that an aircraft experienced was measured as the number of takeoffs between its pushback time and its takeoff time<sup>4</sup>. Based on the results of the causal factors analysis, a queuing model was built that estimates the taxi-out time of an aircraft given an estimate of the takeoff queue size that it may face before takeoff (described in the third section). For each aircraft, the queuing model assumes knowledge of the number of departure aircraft present on the airport surface at its pushback time and estimates its takeoff queue size by predicting the amount of passing that it may experience on the airport surface during its taxi out. The model also takes into account the runway configuration, the airline/terminal and the downstream restriction factors. The prediction performance of the queuing model was compared, as described in the fourth section, to a fourteen-day running average model that represents the taxi-out model currently in use in the Enhanced Traffic Management System (ETMS). The queuing model reduced the mean absolute error in the taxi-out time estimation by one minute from the running average model (4.6 minutes compared to 5.7

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<sup>4</sup> As opposed to the number of aircraft present on the airport surface at a particular time used by Shumsky.

minutes, respectively, for a sample with an average taxi-out time of 19.2 minutes) and improved the accuracy rate (with a 5-minute error margin) by ten percent.

### Analysis of causal factors that affect the taxi-out time

A number of factors cause pushback and taxi-out delays at major airports (Idris et al, 1998, 1999). A model for predicting the taxi-out time should take into account as many of these causal factors as possible; however, only some of them are observable quantitatively.

Based on extensive field observations conducted at Boston Logan Airport (Idris et al 1999, Idris 2001), a number of factors that affect the pushback and taxi-out times were identified. The effect of these factors was analyzed using the Airline Service Quality Performance (ASQP) data. The ASQP data include records of the ACARS<sup>5</sup> pushback time and takeoff time along with other information such as the scheduled departure and arrival times, the aircraft type, the airline, and the origin and destination airports. The pushback time ( $t_{out}$ ) is measured by the ACARS “Out” time, which is recorded by a switch that is activated when the aircraft doors are closed and brakes are released. The takeoff time ( $t_{off}$ ) is measured by the ACARS “Off” time, which is recorded by a switch that is activated when the wheels of the aircraft leave the ground. The taxi-out time ( $T$ ) is measured as the duration between the pushback time ( $t_{out}$ ) and the takeoff time ( $t_{off}$ ) as shown in Equation 1 and in Figure 1. In addition the pushback delay is measured as the duration between the scheduled pushback time and the actual pushback time ( $t_{out}$ ) as shown in Figure 1. The effect of some of the causal factors on the pushback delay was also analyzed and compared to the effect on the taxi-out time. The ASQP database includes ACARS records for the ten major airlines in the US, which constitute approximately 50 percent of the traffic at Logan Airport.

$$T = t_{off} - t_{out} \tag{1}$$

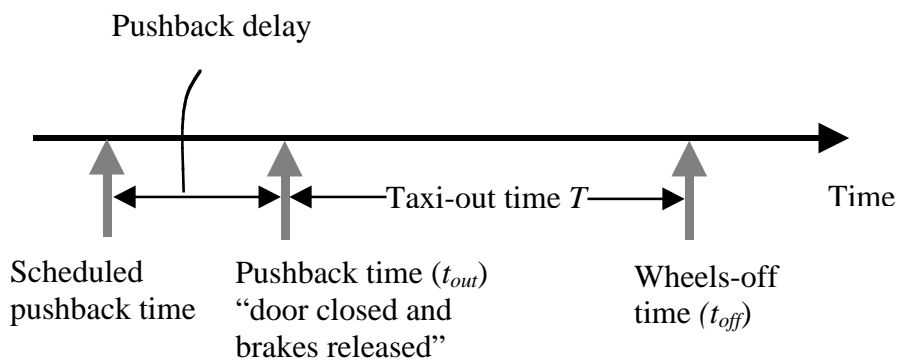


Figure 1: Taxi-out time measured by ACARS “Out” and “Off” time events

<sup>5</sup> ACARS is the Air Carrier Automated Reporting System, which records automatically, by activating switches on the airplane, four time events: The pushback time (Out), the takeoff time (Off), the touchdown time (On) and the time of parking at the gate (In).

The following is a discussion of the main causal factors, the way they were measured, and their absolute and relative importance.

### **Runway configuration**

The runway configuration is the assignment of runways to arrivals and departures, and therefore it determines the flow pattern on the airport surface and in its surrounding airspace. Figure 2 shows the flow pattern under two major runway configurations at Logan Airport: The configuration 27/22L-22R/22L<sup>6</sup> uses runways 27 and 22L for arrivals and runways 22R and 22L for departures; and the configuration 4R/4L-9/4L/4R uses runways 4R and 4L for arrivals and runways 9, 4R and 4L for departures.

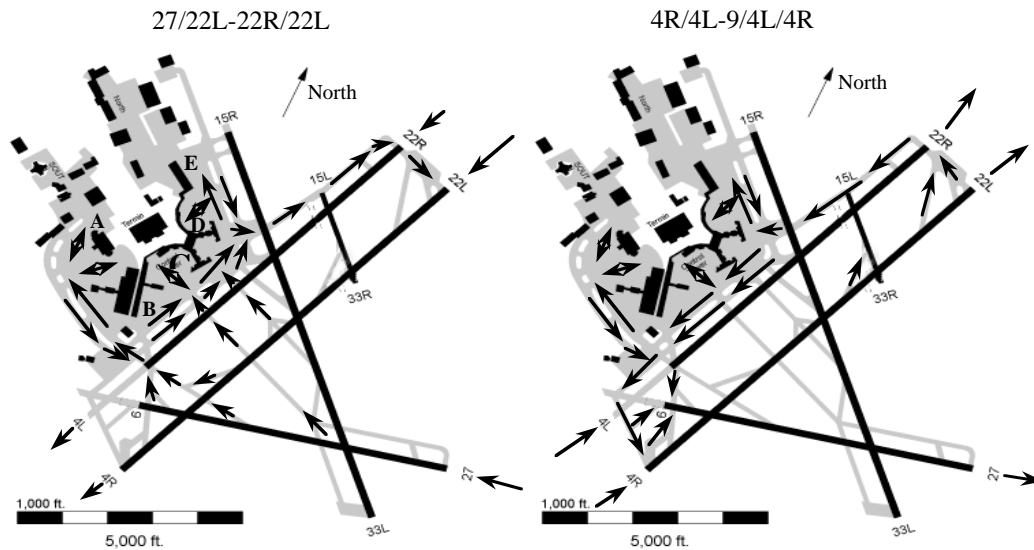


Figure 2: Flow patterns under two runway configurations at Logan Airport

The taxi-out times may be different under different runway configurations due to a number of reasons. These reasons include: the level of interaction between the arrival and departure flows that the runway configuration exhibits, the different distance between the gates (terminal buildings) and the active departure runways, and the different amount of queuing and congestion that results due to the imbalance between the arrival/departure demand and the arrival/departure capacities of the runway configuration.

Runway configuration data were available for Logan Airport through the Preferential Runway Advisory System (PRAS)<sup>7</sup>. Given this data it was possible to analyze the airport taxi-out time

<sup>6</sup> The letters L (short for Left) and R (short for Right) refer respectively to the left runway and the right runway of two parallel runways.

<sup>7</sup> PRAS is a system that advises the use of certain runway configurations at Logan Airport in order to minimize the noise exposure of the surrounding communities, given runway availability, wind, weather and demand constraints (PRAS 1998). Through PRAS, records of the utilization of each runway configuration are maintained in order to measure the airport performance in terms of noise abatement.

under different runway configurations. Figure 3 shows the arrival/departure rate capacity envelopes along with the average taxi-out times for four runway configurations with different capacities. The arrival and departure rates were measured by the ETMS counts<sup>8</sup> of the number of landings and takeoffs in fifteen-minute periods, and the taxi-out time was measured using the ASQP data as given in Equation 1 (see Figure 1). In addition to the different capacity levels of the different runway configurations, Figure 3 shows the coupling between the arrival and departure rate capacities where higher departure rates are achieved at the expense of the arrival rate and vice versa.

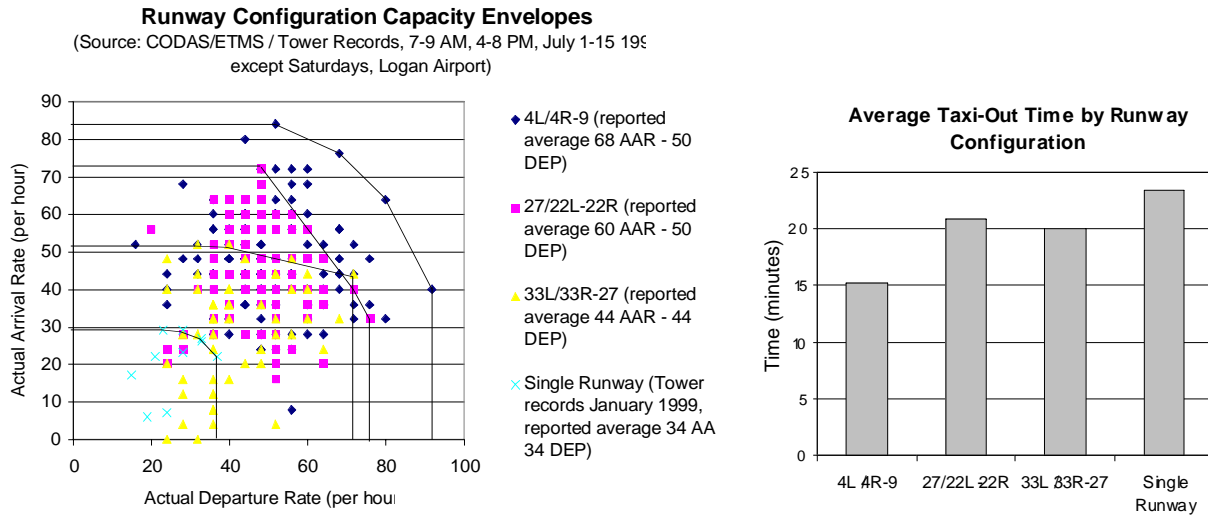


Figure 3: Capacity envelopes and taxi-out time averages under different runway configurations

The difference in the average taxi-out times between the different runway configurations in Figure 3 is an example of the effect of the runway configuration on the taxi-out time. The difference in the taxi-out time is caused by the different capacity levels of the different runway configurations as well as by the different taxi-out distances between the terminal buildings and the departure runways under the different runway configurations. For example, the average taxi-out time is lowest in the runway configuration 4R/4L-9/4L/4R, which has the highest capacity and the smallest taxi-out distance (see Figure 2). It is higher under the two runway configurations 27/22L-22R/22L and 33L/33R-27/33L/33R, which have lower capacity levels as well as longer taxi-out distances. And finally, it is highest under the single-runway configurations, which have the lowest capacity level<sup>9</sup>.

<sup>8</sup> Takeoffs are counted when the radar tracking system captures the aircraft and landings are counted when the aircraft drop off the radar tracking system.

<sup>9</sup> The single-runway configurations were combined in order to increase the sample size (since single runways are used only in infrequent, unfavorable wind and weather conditions). The different single-runway configurations may have different rate capacities and different distances between the terminal buildings and the departure runways. Therefore, the average taxi-out time in Figure 3 may vary between the different single-runway configurations. However overall, it is higher than the average taxi-out time under the higher-capacity runway configurations.

In order to take the effect of the runway configuration on the taxi-out time into account, the analysis of the other factors was conducted and the estimation queuing model was built for specific runway configurations.

### **Airline/terminal**

Within one runway configuration, the taxi-out time varies due to a number of other factors. One important factor is the distance between the gate from which the aircraft pushes back and the runway from which it takes off. While gate data were not available, knowledge of the airline is an indication of the distance since at most airports, and particularly at Logan Airport, the airlines are concentrated in specific terminal buildings (see Figure 4). In addition to distance, the airline/terminal may also reflect other factors that cause taxi-out delays, such as complex terminal building geometry, which may include narrow alleys, and airline/pilot specific behavior.

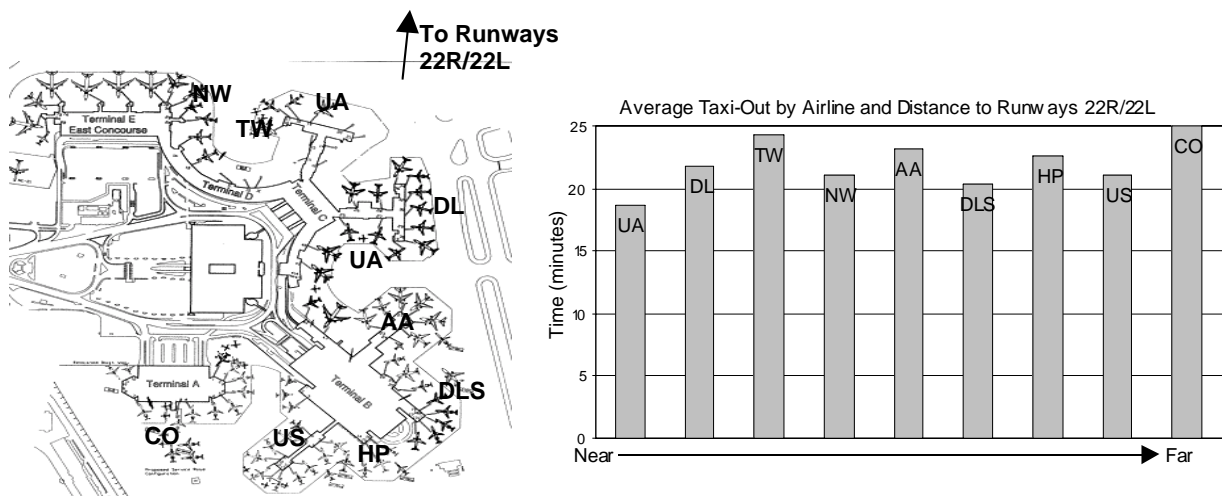


Figure 4: Effect of distance on taxi-out time<sup>10</sup>

Figure 4 compares the average taxi-out time between different airlines in the 27/22L-22R/22L runway configuration at Logan Airport. In most cases the average taxi-out time increased as a function of the distance to the departure runways 22R/22L. The taxi-out time was also correlated with the airline/terminal factor in a linear regression analysis. The resulting  $R^2$  value was 0.02 indicating that the distance is one positive factor; however, it does not significantly account for the variability in the taxi-out time.

### **Weather and downstream restrictions**

Weather reduces the capacity of the airport system by impeding the flow through weather-impacted resources, such as runways and exit fixes<sup>11</sup>. In order to analyze the weather factor, a number of weather measurements were used. The reported weather forecast for each day and the

<sup>10</sup> DLS = Delta Shuttle. Since Delta Shuttle flights (only to LGA in 1998) fly out of a different terminal from other Delta flights, they are treated as a separate airline both here and in the model.

<sup>11</sup> Exit fixes are gates from which the outbound traffic leaves the terminal airspace into the Center airspace.

reported meteorological conditions in terms of Visual Flight Rule (VFR) and Instrument Flight Rule (IFR) conditions did not indicate a strong correlation with the taxi-out time. The most indicative measure of the weather factor were the downstream restrictions, which are flow management programs imposed on the departure traffic heading to weather-impacted destination airports, jet routes or exit fixes. Downstream restrictions may be imposed due to causes other than weather, such as high traffic volume or equipment outages; however, weather is usually the main cause (Idris 2001).

An analysis of aircraft from July 1998 that suffered different types of downstream restrictions<sup>12</sup> provided insight into the effect of downstream restrictions on the taxi-out time as well as on the pushback delay for comparison (see Figure 1 for how the two times are measured) (Idris, 2001). The mean and standard deviation of the taxi-out and the schedule-to-pushback times are displayed in Figure 5 for unrestricted aircraft and aircraft that suffered one of six different types of restrictions: Ground Stop (GS<sup>13</sup>), Expected Departure Clearance Time (EDCT<sup>14</sup>), Departure Sequencing Program (DSP<sup>15</sup>) and In-Trail<sup>16</sup> restrictions. The Ground Stop and Miles in Trail (MIT) restrictions were imposed either for destination airports or locally through exit fixes in the terminal airspace. For taxi restrictions, a departure aircraft was considered restricted if there was an overlap between its taxi-out time and the duration of the restriction<sup>17</sup>. Similarly, for the pushback restrictions, a departure aircraft was considered restricted if there was an overlap between the duration between its scheduled and actual pushback times and the duration of the restriction. The difference between each sample's mean and the no-restriction sample mean was tested and the results are summarized in Table 1.

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<sup>12</sup> Downstream restrictions data were obtained from the Control Tower logs of imposed flow management programs.

<sup>13</sup> For short-term effect, the command center (ATCSCC) uses the Ground Stop (GS) restriction to stop all departures to an affected NAS location until further notice.

<sup>14</sup> EDCT is a long term Ground Delay Program (GDP), in which the command center (ATCSCC) selects certain flights heading to a capacity limited destination airport and assigns an Expected Departure Clearance Time (EDCT) to each flight, with a 15-minute time window.

<sup>15</sup> Departure Sequencing Program (DSP) is a program designed to assist in achieving a specified interval for departures over a common point (such as a fix). In order to achieve the specified interval over the common point a DSP wheels-off time (with a 3-minute window) is assigned by the center (ARTCC) to each affected aircraft such that it arrives at the common point in a given time slot.

<sup>16</sup> Miles-in-Trail/Minutes-in-Trail restrictions are imposed in terms of spacing (miles/minutes) between departure aircraft, associated with the same destination or route of flight.

<sup>17</sup> All samples included aircraft affected by a single type of restriction. Since no information on the exit fix assigned to an aircraft was available in the ASQP data, a conservative assumption was made that local restrictions (imposed on outbound traffic through exit fixes) affected all aircraft which were taxiing during the restriction (for the effect on taxi-out time) and which were scheduled to pushback during the restriction (for the effect on pushback delay).



**Downstream Restriction Effects on Delays**  
 (Source: ASQP data, Restriction logs, Logan Airport, July 1998)

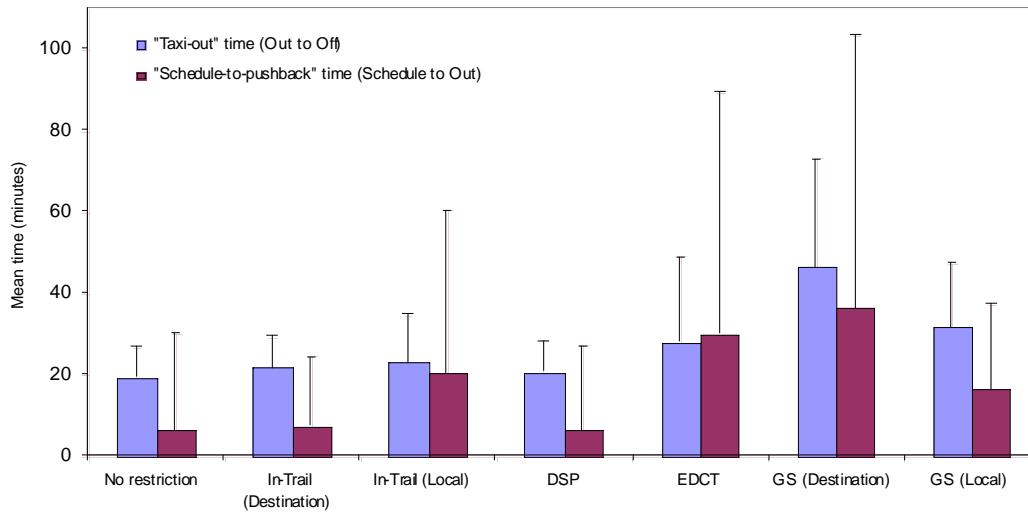


Figure 5: Downstream restrictions effect on the taxi-out time and pushback delay

Restriction type	Mean "taxi-out" (min)	Standard deviation (min)	p-value (mean difference with No restriction)	Observations
No restriction	19.3	7.3		6896
In-Trail (Destination)	21.6	7.9	0.006	78
In-Trail (Local)	22.9	11.9	1.90E-08	342
DSP	20.6	7.9	0.002	329
EDCT	27.9	21	0.007	39
GS (Destination)	46.4	26.5	7.40E-06	27
GS (Local)	31.7	15.7	1.50E-07	55

Restriction type	Mean "schedule-to-pushback" (min)	Standard deviation (min)	p-value (mean difference with No restriction)	Observations
No restriction	6.4	23.7		6983
In-Trail (Destination)	7.3	17.2	0.34	60
In-Trail (Local)	20.3	40	6.60E-10	325
DSP	6.2	20.7	0.45	298
EDCT	30.1	59.2	0.008	39
GS (Destination)	36.3	67.2	0.007	34
GS (Local)	16.5	20.7	0.001	41

Table 1: Downstream restrictions effect on the taxi-out time and pushback delay

As shown in Figure 5, the taxi-out time and its variability increased significantly for the aircraft that were affected by downstream restrictions. The Ground Stop restrictions that were imposed on the outbound flow to destination airports and through local exit fixes caused the most pronounced delays. The Ground Delay Program, EDCT restrictions also showed a significant delay effect on the taxi-out time. However, the EDCT effect was particularly evident on the schedule-to-pushback time, which is expected since the Ground Delay Programs are long-term restrictions that are usually absorbed by holding the aircraft on their gates before pushback.

## Departure demand and queue size

Large queues form on the airport surface, particularly in departure rush times, when the departure demand exceeds the departure capacity of the runway system. During its taxi-out an aircraft spends some time taxiing between the gate and the runway, some time holding to absorb any imposed delays (by downstream restrictions for example), and some time queuing behind other aircraft waiting to use the departure runway. Therefore, the long queues are a major factor in causing long taxi-out times. The long departure queues are caused by the imbalance between the demand and the capacity, which is caused by increased demand and reduced capacity. On the demand side, during high-demand hours airlines schedule more departures than the capacity of the airport. Capacity factors include the runway configuration and the downstream restrictions as explained in the previous two factors that affect the taxi-out time. For example, the congestion is increased when lower capacity runway configurations are used and when downstream restrictions are imposed on outbound traffic through weather-impacted exit fixes.

In order to analyze the effect of the departure queue size on the taxi-out time, the queue size was measured in a number of ways. Regression analysis revealed that the correlation of the taxi-out time with the queue size as measured by the schedule<sup>18</sup> was low ( $R^2$  less than 0.03). The correlation was also low between the taxi-out time of an aircraft and the number of departure aircraft ( $N$ ) that were present on the airport surface at the pushback time of the aircraft ( $R^2 = 0.19$ , see Figure 6). The number of departure aircraft ( $N$ ) that are present on the airport surface at the pushback time ( $t_{out}$ ) of a particular aircraft was measured as the number of aircraft that had pushed back but had not yet taken off at that aircraft's pushback time.

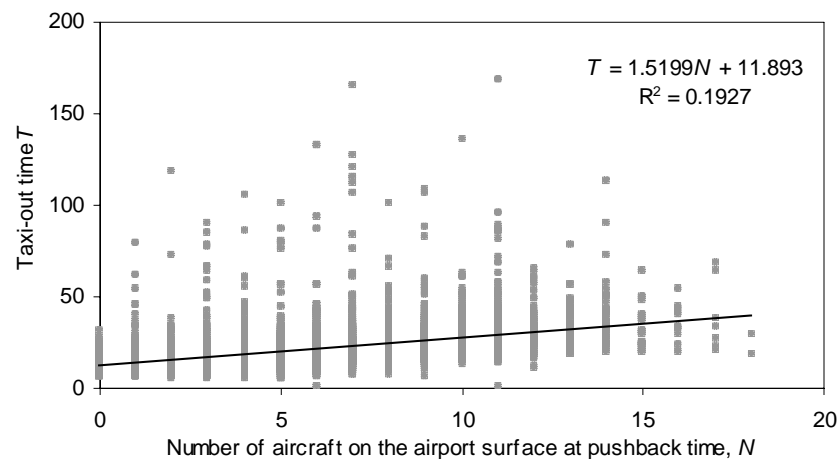


Figure 6: Taxi-out time correlation with the number of aircraft ( $N$ ) on the surface at pushback

The low correlation indicates that the number of departure aircraft ( $N$ ) present on the airport surface at the pushback time of an aircraft does not measure accurately the size of the takeoff queue that the aircraft faces. This is due primarily to the passing between aircraft that takes

<sup>18</sup> Using the schedule, the level of congestion affecting a particular aircraft was measured by the number of departures scheduled to pushback during a time window (from 10 to 45 minutes) surrounding the pushback time of that particular aircraft.

place on the airport surface. While the air traffic controllers attempt to maintain a First-Come-First-Serve (FCFS) sequence of takeoffs they deviate from it in many circumstances and allow passing between aircraft. For example, an aircraft may be allowed to pass other aircraft already existing on the taxiway system if the aircraft is an emergency and has to be expedited, or has an assigned takeoff time, or if some of the existing aircraft are suspended absorbing long delays. Passing may also be allowed due to the different distances between the gates and the departure runways and due to the sequencing strategies of the air traffic controllers, which may deviate from the FCFS sequence in order to improve efficiency and workload (Idris 2001). Because of this passing, the  $N$  departure aircraft that are on the airport surface when an aircraft pushes back are not exactly the same aircraft that takeoff ahead of it as depicted in Figure 7.

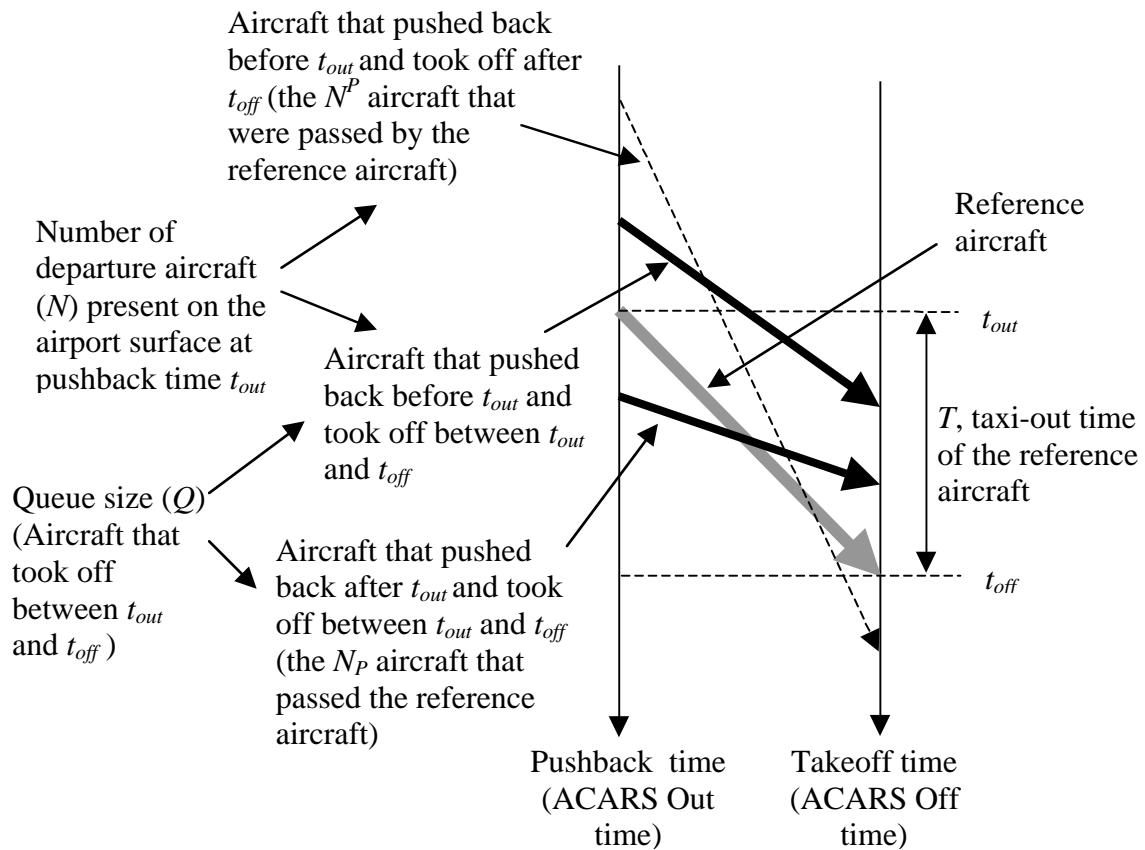


Figure 7. The queue size  $Q$  and the passing effect

Figure 7 shows the relationship between the number of departure aircraft ( $N$ ) that were present on the airport surface at the pushback time ( $t_{out}$ ) of a particular reference aircraft and the number of takeoffs ( $Q$ ) that took place ahead of the reference aircraft during its taxi out. The taxi-out time of an aircraft is depicted in Figure 7 as an arrow extending from its pushback time to its takeoff time (both known from the ASQP data). The  $N$  aircraft that had pushed back but had not taken off yet before the pushback time ( $t_{out}$ ) of the reference aircraft are divided into two groups: A number ( $N^P$ ) of the  $N$  aircraft took off later than the takeoff time ( $t_{off}$ ) of the reference aircraft; these aircraft were passed by the reference aircraft and therefore did not queue for takeoff ahead

of it. The rest of the  $N$  aircraft took off before the takeoff time ( $t_{off}$ ) of the reference aircraft and therefore they constituted a part of the takeoff queue ahead of it. In addition, a number ( $N^P$ ) of aircraft pushed back later than the pushback time ( $t_{out}$ ) of the reference aircraft, passed the reference aircraft and took off ahead of it; these aircraft also formed another part of the takeoff queue ahead of the reference aircraft. Therefore, a better measurement of the size of the takeoff queue that the reference aircraft faced is the number of takeoffs ( $Q$ ) that took place during its taxi out. The queue size ( $Q$ ) is related to the number of departure aircraft ( $N$ ) that were present on the airport surface at the pushback time ( $t_{out}$ ) of the reference aircraft by the following equation:  $Q = N - N^P + N_p$ .

The correlation of the taxi-out time with the takeoff queue size ( $Q$ ) improved significantly over its correlation with the number of departure aircraft ( $N$ ) that were present on the airport surface at pushback time (Idris, 2001). The correlation improved from  $R^2 = 0.19$  to  $R^2 = 0.59$  as shown in Figure 8.

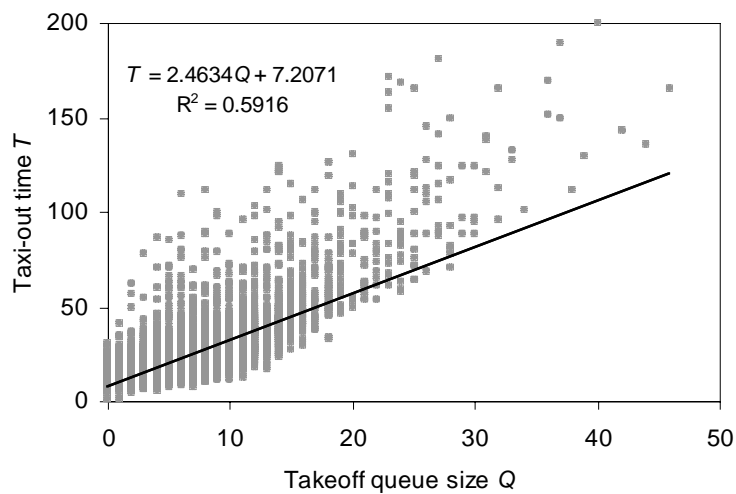


Figure 8: The takeoff queue size effect on the taxi-out time

### **Other factors**

A linear regression between the taxi-out time and the aircraft type indicated that the aircraft type was not a major factor in affecting its taxi-out time ( $R^2 = 0.01$ ).

A linear regression also showed that the arrival demand, measured by the number of arrivals that landed or the number of arrivals that parked at the gate in a time window around the pushback time of a taxiing aircraft, had a low correlation with the taxi-out time of the taxiing aircraft ( $R^2$  less than 0.02).

## Queuing model for taxi-out time estimation

Based on the analysis of causal factors in the previous section, it was concluded that the takeoff queue is the main factor that explains the taxi-out time. Therefore, a queuing model was built and used to predict the taxi-out time based on queue size estimation. The queuing model predicts the taxi-out time ( $T$ ) of an aircraft given an estimate of the takeoff queue size ( $Q$ ) that it may face,  $T = f(Q)$ . The model assumes that the number of departure aircraft ( $N$ ) present on the airport surface at the aircraft's pushback time is known and estimates the queue size ( $Q$ ) given  $N$  by predicting the passing that the aircraft may experience before takeoff. In order to estimate the taxi-out time ( $T$ ) of an aircraft from the known number of departure aircraft ( $N$ ) present on the airport surface at its pushback time, mappings between  $N$  and  $Q$  and between  $T$  and  $Q$  were developed from 3 months of historic ASQP data (May, June and July, 1998).

Based on the causal factor analysis, the taxi-out time is affected by other factors including the runway configuration, the airline/terminal and the downstream restrictions. The runway configuration and airline/terminal factors were taken into account by building different models for each combination of runway configuration and airline. The data set, which contained 26302 flights, had 7 runway configurations and 8 airlines, which resulted in 56 different subsets<sup>19</sup>. The downstream restrictions were accounted for indirectly by taking passing into account (aircraft that are held on the taxiway system for a long time due to restrictions experience long takeoff queue sizes as shown in Figure 9, mainly because they are passed by many other departure aircraft that takeoff ahead of them (Idris 2001)). A portion of the flights that incurred excessive taxi-out delays<sup>20</sup> was also removed.

For each subset, a mapping of  $T$  and  $Q$  was developed.  $T$  was calculated as in Equation (1) and  $T(Q)$  was derived by fitting a second order equation to the map (see Figure 9).

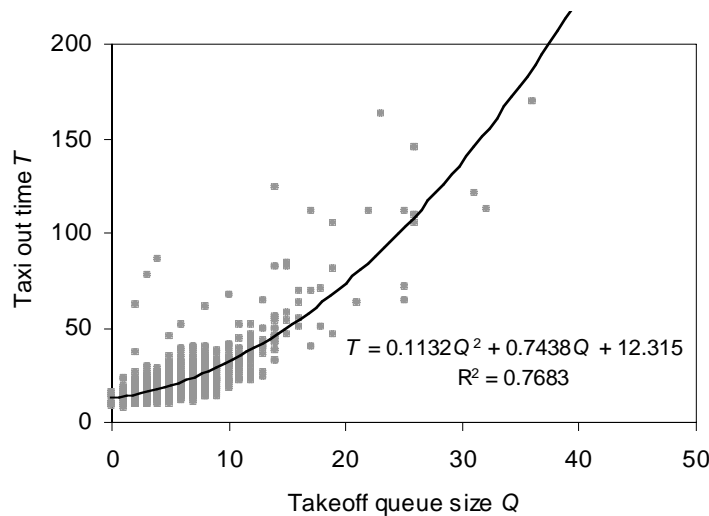


Figure 9:  $T(Q)$  for configuration 27/22L-22R/22L and American Airlines

<sup>19</sup> Delta and Delta Shuttle were considered different airlines because they occupy different terminal building.

<sup>20</sup> Outliers removed included data points in the highest 1% (taxi-out times above 200 minutes, and queues above 65 aircraft).

For each subset, a probability density distribution<sup>21</sup> was developed, giving the probability that a queue size  $Q$  may develop starting from  $N$  departure aircraft on the airport surface at pushback:  $P(Q | N)$ . Figure 10 shows examples of  $P(Q | N)$  for  $N = 0$  through 4 aircraft. As  $N$  takes on higher values, the range of possible values for  $Q$  increases.

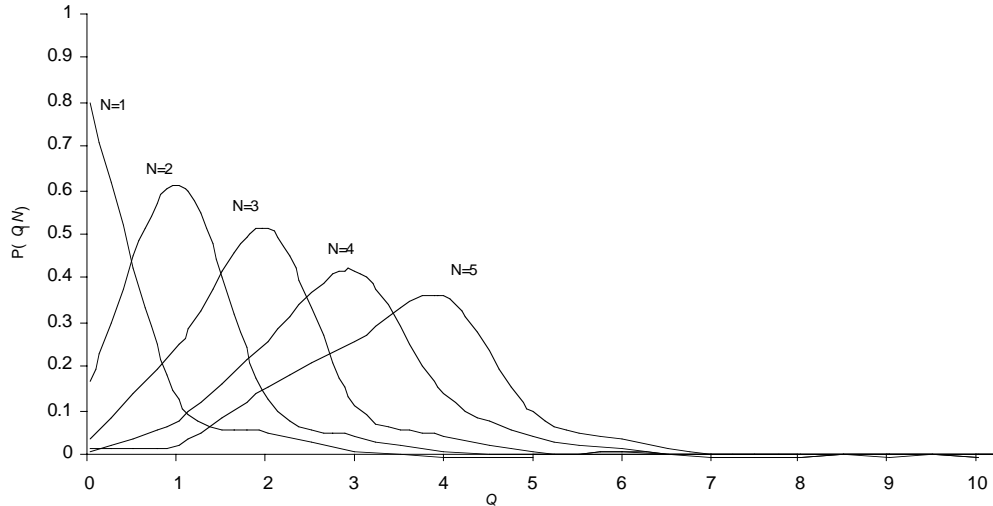


Figure 10: The distributions  $P(Q | N)$  for configuration 4R/4L-9/4R/4L and US airlines

Then given  $N$ , the number of aircraft on the airport surface at pushback time, an average taxi-out time  $\bar{T}(N)$  over all possible queue-size values  $Q$ , was calculated as shown in Equation 2.

$$\bar{T}(N) = \sum_Q [T(Q) * P(Q | N)] \quad (2)$$

Finally, a second-order equation was fitted to the  $\bar{T}(N)$  values resulting in a model  $T(N)$  for each of the runway configuration-airline combinations (see Figure 11).  $R^2$  ranged from .996 to 1 for all models.

<sup>21</sup> Gamma distributions were fitted to the discrete curves. However, the model returned a lower success rate when the Gamma distributions were used as opposed to the actual discrete probabilistic mappings. Higher values of  $N$  had too few data points to accurately fit a distribution. At lower values of  $N$ , differences between the Gamma distributions and the actual curves contributed greatly to the model, since lower values of  $N$  occurred more frequently. The model discussed here uses the actual discrete probabilistic mappings.

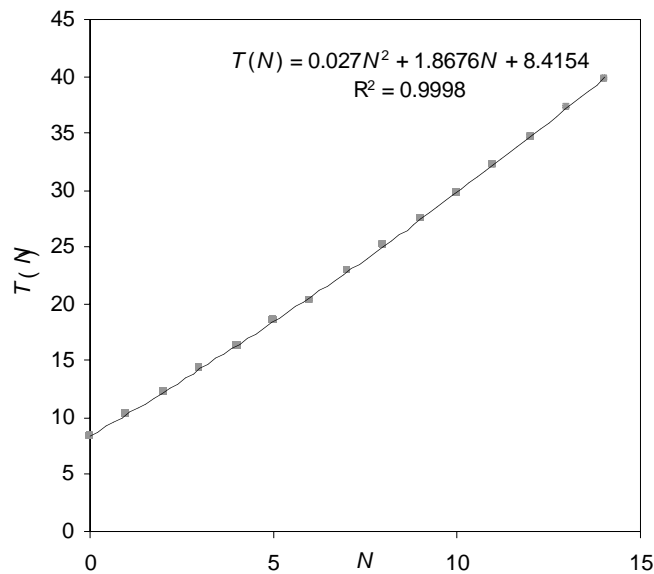


Figure 11:  $T(N)$  for configuration and 4R/4L-9/4R/4L and Continental Airlines

The prediction performance of the queuing model was then compared to a running average model as described in the next section.

## Prediction performance

The prediction accuracy of the model developed was tested by estimating the taxi-out time of the flights reported in the ASQP data in the month of August 1998.

For each aircraft in the month of August 1998,  $N$  was calculated as the number of aircraft that had pushed back but had not taken off yet by its pushback time. Then given the airline of the aircraft and the runway configuration at the time, the corresponding  $T(N)$  mapping (developed from the historical data as described in the previous section) was used to estimate its taxi-out time.

A running average model was developed for comparison. This model represents the method used currently in the Enhanced Traffic Management System (ETMS). ETMS uses the average taxi-out time of the fourteen preceding occurrences for a given flight<sup>22</sup> to predict its taxi-out time (ETMS 2000). No other factors, such as the runway configuration or weather, are taken into account. Instead of the ETMS measurement of the takeoff time, which is based on the first time the aircraft is captured by the radar tracking system, the ACARS wheels off time reported in the ASQP data was used. Similarly, the ACARS out time was used as a measurement of the pushback time instead of the scheduled (or airline updated) pushback time used by ETMS. Since the ACARS measurements of the takeoff and pushback times are more accurate than the ETMS

<sup>22</sup> Only filed flights (flights that filed a flight plan) are included in the running average model. For non-reported flights, ETMS creates an estimate based on three factors: the day of the week, the time of the day and the duration of the flight.

takeoff and scheduled pushback times (respectively), the running average model developed in this paper is a conservative baseline.

The prediction accuracy of the queuing model was compared to the running average model for the flights reported in the ASQP data in the month of August 1998. As shown in Table 2, the mean absolute error of the queuing model was 4.6 minutes compared to 5.7 minutes for the running average model<sup>23</sup>. The queuing model was able to predict 66% of the taxi-out times within 5 minutes of the actual time. The running average model was able to predict 54% of the taxi-out times within the same error margin. Using a 15-minute error margin, the queuing model had an accuracy rate of 96%, while the running average model had an accuracy rate of 94%.

	Running Average	Queuing Model
Mean absolute difference between actual and predicted taxi	5.69 minutes	4.56 minutes
% predicted within 5 minutes of actual taxi	53.74%	65.63%

Table 2: Prediction accuracy of the queuing model compared to the running average

Significance tests<sup>24</sup> performed on the predicted values for both models compared their similarity to actual times and to each other. The results are shown in Table 3. The queuing model and the running average model are statistically significantly different from each other. In addition, the predicted values from the running average model are statistically significantly different from the actual values for the sample of August.

Group	t Value	Prob > t	95% Confidence Interval for Difference of Means	
			Lower Limit	Upper Limit
Actual - Running Avg	-10.66	<.0001	-1.46	-1.00
Actual - Queuing Model	-0.848	0.3966	-0.30	0.12
Running Avg - Queueing Model	-14.21	<.0001	-1.30	-1.00

Table 3: Significance tests

## Conclusions and extensions

In order to determine the main causal factors that affect the taxi-out time, an analysis of a number of factors was conducted at Logan Airport. The main causal factors identified were the runway configuration, the airline/terminal, the downstream restrictions (which reflect mainly the

<sup>23</sup> The average taxi-out time for the sample was 19.20 minutes.

<sup>24</sup> Tests were conducted at a significance level of 0.05. A high t-value indicates that the difference in means is significant. However, a low t-value does not indicate that the difference in means is insignificant. A better indicator of significance is the confidence interval.



weather factor), and the demand factor measured as the takeoff queue size. Of these factors, the queue size correlated best with the taxi-out time, especially when the queue that each aircraft experienced was measured as the number of takeoffs between its pushback time and its takeoff time.

Based on the analysis of the causal factors, a queuing model was built that estimates the taxi-out time of an aircraft given the number of departure aircraft present on the airport surface at its pushback time. For each aircraft, the queuing model assumes knowledge of the number of departure aircraft present on the airport surface at its pushback time and estimates the size of the takeoff queue that it may face by predicting the amount of passing that it may experience on the airport surface during its taxi out. A different model was built for each combination of runway configuration and airline. By taking passing into account, the excessive taxi-out times caused by long suspensions (due for example to downstream restrictions) were explained by larger takeoff queue sizes. The performance of the queuing model in predicting the taxi-out time was compared to a fourteen-day running average model. The running average model represented the baseline currently in use in the Enhanced Traffic Management System (ETMS). The queuing model reduced the mean absolute error in the taxi-out time estimation by one minute from the running average model (4.6 minutes compared to 5.7 minutes, respectively, for a sample with an average taxi-out time of 19.2 minutes) and improved the accuracy rate (with a 5-minute error margin) by ten percent.

The model developed in this paper is applicable when the number of aircraft present on the airport surface at pushback time is known. Therefore, the model has direct implications and use in tactical applications such as the Surface Movement Advisor (SMA). For more strategic flow management applications, where the taxi-out time prediction is needed a certain time in advance of the pushback time, a flow model is required to predict the number of aircraft on the surface at the scheduled pushback time. This model is under development.

The model developed in this paper is also applicable under specific runway configurations. Since the runway configuration is unknown at the future time of the taxi-out time prediction, the model may be extended with a runway configuration predictor. A runway configuration typically runs for several hours and in some cases its change may be predicted accurately based on predictable wind direction and common procedures such as noise abatement.

The model developed in this paper can also be extended with a model of the pushback delay (schedule-to-pushback time). Efforts to generate a pushback delay model have been attempted (see for example Shumsky 1995 and Andersson 2000). Such a model should take into account factors like the downstream restrictions, which was shown in this paper to have a clear and larger impact on the pushback delay than on the taxi-out time (since affected aircraft are typically held on their gates). Efforts to extend and integrate a pushback delay model are also underway.

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