Queuing Models of Airport Departure Processes for Emissions Reduction

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Aircraft taxiing on the surface contribute significantly to the fuel burn and emissions at airports. This paper investigates the possibility of reducing fuel burn and emissions from surface operations through a reduction of the taxi times of departing aircraft. A novel approach is proposed that models the aircraft departure process as a queuing system, and attempts to reduce taxi times and emissions through improved queue management strategies.

The departure taxi (taxi-out) time of an aircraft is represented as a sum of three components, namely, the unimpeded taxi-out time, the time spent in the departure queue, and the congestion delay due to ramp and taxiway interactions. The dependence of the taxi-out time on these factors is analyzed and modeled. The performance of the model is validated through a comparison of its predictions with observed data at Boston's Logan International Airport (BOS). The reductions in taxi-out times from the proposed queue management strategy are translated to reductions in fuel burn and emissions using ICAO engine models for the taxi phase of the flight profile.

Nomenclature

PS	Pushback schedule
RC	Runway configuration
MC	Meteorological conditions
GL	Gate location of a departing flight
$P(t)$	Number of aircraft pushing back during time period t
$N(t)$	Number of departing aircraft on the surface at the beginning of period t
$Q(t)$	Number of aircraft waiting in the departure queue at the beginning of period t
$R(t)$	Number of departures on the surface not at the departure queue at the beginning of period t
$C(t)$	Departure capacity of the departure runways during period t
$T(t)$	the number of takeoffs during period t
$NQ_{(i)}$	Number of takeoffs between the pushback time and takeoff time of aircraft i
$\tau(i)$	Taxi time of departing aircraft i
$\tau_{unimped}(i)$	Unimpeded taxi-out time of aircraft i
$\tau_{taxiway}(i)$	Delay to aircraft i due to aircraft interactions on the ramp and the taxiways
$\tau_{dep.queue}(i)$	Time aircraft i spends in the departure queue
N^*	Saturation point for a segment
N_{cntrl}	Critical N at which aircraft are held in the *virtual departure queue*

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I.   Introduction

Aircraft taxi operations contribute significantly to the fuel burn and emissions at airports. The quantities of fuel burned as well as different pollutants such as Carbon Dioxide, Hydrocarbons, Nitrogen Oxides, Sulfur Oxides and Particulate Matter (PM) are a complicated function of the taxi times of aircraft, in combination with other factors such as the throttle settings, number of engines that are powered, and pilot and airline decisions regarding engine shutdowns during delays. In 2007, aircraft in the United States spent more than 63 million minutes taxiing in to their gates, and over 150 million minutes taxiing out from their gates;[9] in addition, the number of flights with large taxi-out times (for example, over 40 min) has been increasing (Table 1). Similar trends have been noted at major airports in Europe, where it is estimated that aircraft spend 10-30% of their flight time taxiing, and that a short/medium range A320 expends as much as 5-10% of its fuel on the ground.[7]

Table 1: Taxi-out times in the United States, illustrating the increase in the number of flights with large taxi-out times between 2006 and 2007

Year	Number of flights with taxi-out time (in min)						
	< 20	20-39	40-59	60-89	90-119	120-179	≥ 180
2006	6.9 mil	1.7 mil	197,167	49,116	12,540	5,884	1,198
2007	6.8 mil	1.8 mil	235,197	60,587	15,071	7,171	1,565
Change	-1.5%	+6%	+19%	+23%	+20%	+22%	+31%

Table 2: Top 10 airports with the largest taxi-out times in the United States in 2007[23]

Airport	JFK	EWR	LGA	PHL	DTW	BOS	IAH	MSP	ATL	IAD
Avg. taxi-out time (in min)	37.1	29.6	29.0	25.5	20.8	20.6	20.4	20.3	19.9	19.7

Operations on the airport surface include those at the gate areas/aprons, the taxiway system and the runway systems, and are strongly influenced by terminal-area operations. The different components of the airport system are illustrated in Figure 1. These different components have aircraft queues associated with them and interact with each other. The cost per unit time spent by an aircraft in one of these queues depends on the queue itself; for example, an aircraft waiting in the gate area for pushback clearance predominantly incurs flight crew costs, while an aircraft taxiing to the runway or waiting for departure clearance in a runway queue with its engines on incurs additional fuel costs, and contributes to surface emissions.
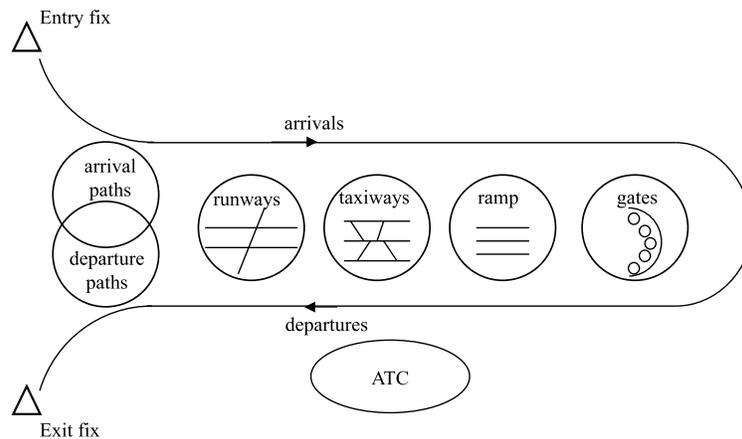
Figure 1: A schematic of the airport system, including the terminal-area.[15]

The *taxi-out time* is defined as the time between the actual pushback and takeoff. Nominally, this quantity is representative of the amount of time that the aircraft spends on the airport surface with engines on, and includes the time spent on the taxiway system and in the runway queues. As a result, surface emissions

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from departures are closely linked to the taxi-out times. At several of the busiest airports, the taxi times are large, and tend to be much greater than the unimpeded taxi times for those airports (Figure 2). It is therefore reasonable to hypothesize that by addressing the inefficiencies in surface operations, it may be possible to decrease taxi times and surface emissions. This was the motivation for prior research on the Departure Planner.[11]
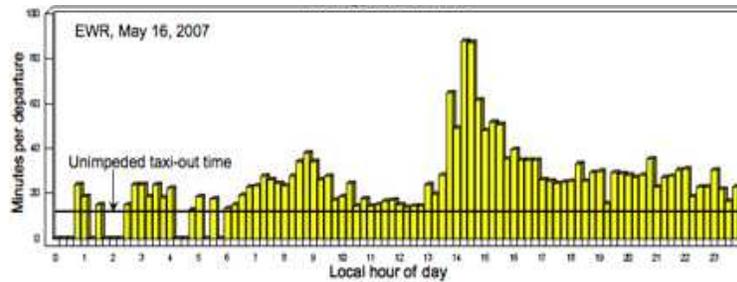
Figure 2: The average departure taxi times at EWR over 15-minute intervals and the unimpeded taxi-out time (according to the ASPM database) from May 16, 2007. We note that large taxi times persisted for a significant portion of the day.[9]

In this paper, we consider a promising approach toward reducing emissions at airports, namely, reducing taxi times by limiting the build up of queues and congestion on the airport surface through improved queue management. Under current operations, aircraft spend significantly longer lengths of time taxiing out during congested periods of time than they would otherwise. By improving coordination on the surface, and through information sharing and collaborative planning, we believe that aircraft taxi-out procedures can be managed to achieve considerable reductions in fuel burn and emissions.

In order to describe quantitatively how queues form on the surface and what factors lead to the increased taxi-out times which are observed, we develop a queuing model of the departure process. We validate this model in terms of its ability to predict taxi-out times and the flow of aircraft on the ground at a particular airport, Boston Logan International Airport (BOS). We then explain how this model can be used to determine improved queue management strategies and estimate the potential benefits of this approach. Finally, we also assess the operational barriers that need to be addressed before it can be adopted.

A.   Related work

Prior work on the modeling of the departure process at airports can be broadly classified into two groups. The first group focuses on computing runway-related delays under dynamic and stochastic conditions.[17, 18] This runway-centric approach is justified by the observation that the main throughput bottleneck at an airport is the runway system.[14] This approach views the runway complex of an airport as a queuing system whose customers are aircraft that need to land or takeoff. The models are then used to predict the expected system behavior, and their results are typically most useful for long-term planning (for example, estimating the expected reduction in delays from the construction of a new runway), but are less useful for predicting taxi-out times for individual flights.

The second category of prior research focused on predicting taxi-out times. Shumsky developed a model to predict taxi times using a variety of explanatory variables such as the airline, the departure runway and departure demand.[22] He also developed a queuing model for the runway service process. However, the queuing model was based on cumulative behavior and did not reflect the stochastic nature of the process.[22] Idris *et al.* analyzed the main causal factors that affect taxi times and based on this analysis, they developed a statistical regression model to predict taxi times.[12] This work, however, did not explicitly model the runway service process, and required knowledge of the number of aircraft on the ground in order to predict taxi times. It could therefore not be used for strategic flow management applications such as the one considered in this paper, where we like to consider gate-to-runway traffic states, and determine how surface queues can be managed in order to reduce taxi-out times.

While the above papers identified several key factors that influence taxi-out times, they did not develop a model that was capable of predicting taxi-out times. In contrast, Pujet *et al.* extended some these notions to predict taxi times using a simple queuing model.[20] They assumed that an aircraft will need a certain

(fixed) amount of time, defined to be the *travel time*, to reach the departure runways. In their model, upon reaching the departure runways, aircraft line up in the *runway queue*, where they get served by the runway server according to a probabilistic service process. Pujet *et al.* estimated the travel time for each flight based on several casual factors and also modeled the probabilistic service process. Given a pushback schedule, their model estimated taxi-out time as the sum of travel time and the wait time for service (takeoff) at the runway queue.

This paper provides a better method for estimating the travel times of aircraft to the departure runways and also provides a better model of the service process at the runways. A key objective of this paper is to develop a good predictive model of airport operations that will also reflect a fact that several researchers have observed, but that as yet remains unmodeled, namely that, although the runway is the main flow constraint in departure processes, *the airport is a complex system of interacting queues*.[13]

II. Model inputs and outputs

The primary objective of this paper is to develop a model that adequately describes the departure process, given operations data from an airport. The desired outputs of such a model include:

- The level of congestion on the airport surface in the immediate future.

- The predicted loading of the different surface queues.

- The predicted taxi-out time of each departing flight.

The inputs to the model are based on the explanatory variables identified in previous studies.[1,5,12,22] Idris *et al.*[12] identified the runway configuration, weather conditions and downstream restrictions, the gate location, and the length of the takeoff queue that a flight experiences as the critical variables determining the taxi time of a departing flight. The length of the takeoff queue experienced by a flight is defined as *the number of takeoffs which take place between the pushback time of an aircraft and its takeoff time.*

The present study is an attempt to construct a predictive model of surface congestion, so the takeoff queue size is not available as an input. Instead, we use the pushback schedule, which is the schedule of aircraft pushing back from their gates. We note that we do not predict the pushback schedule based on the published departure schedule; such models that predict pushback schedules based on the departure schedule may be found in Shumsky's thesis.[22] Furthermore, the general weather conditions (denoted either Visual Meteorological Conditions, or Instrumental Meteorological Conditions) are used as surrogates for weather and downstream airspace conditions. Andersson *et al.* introduced the concept of the *segment*, which they defined as a particular combination of runway configuration and weather conditions.[1] The runway configuration is characterized by both the runways used for arrivals as well as those used for departures. Each segment is defined as a combination of the runway configuration and the general weather conditions (VMC or IMC).Therefore, we denote a segment as (Weather Conditions; Arrival Runways | Departure Runways). For example, a segment denoted '(R1,R2 | R3,R4; VMC)' would correspond to runways R1 and R2 being used for arrivals, and R3 and R4 being used for departures under Visual Meteorological Conditions.

To summarize, the inputs to the model are

- The pushback schedule, PS.

- The gate location of the departing flight, GL.

- The segment in use, $(RC; MC)$, expressed as the combination of the runway configuration, RC, and the general weather conditions, MC.

We define

- $P(t)$ = the number of aircraft pushing back during time period t. $P(t)$ is an input to the model.

- $N(t)$ = the number of departing aircraft on the surface at the beginning of period t. $N(t)$ is the first output of the model, indicating the congestion of departing aircraft on the ground.

- $Q(t)$ = the number of aircraft waiting in the departure queue at the beginning of period t. The departure queue is defined as the queue which is formed at the threshold(s) of the departure runway(s), where the aircraft queue for takeoff. $Q(t)$ is the second output of the model, and gives the loading of the departure queues.

- $R(t)$ = the number of departing aircraft taxiing in the ramp and the taxiways at the beginning of period t (*i.e.*, the number of departures on the surface that have not reached the departure queue).

- $C(t)$ = the (departure) capacity of the departure runways during period t.

- $T(t)$ = the number of takeoffs during period t.

- $N_Q(i)$ = the number of aircraft taking off between the pushback and takeoff time of aircraft i (the length of the takeoff queue experienced by aircraft i queue[12]).

- $\tau(i)$ = the taxi time of each departing aircraft. This is the third output of the model.

Using the above notation, the following relations are satisfied:

$$N(t) = Q(t) + R(t) \tag{1}$$
$$N(t) = \min(C(t), Q(t)) \tag{2}$$
$$N(t) = N(t-1) + P(t-1) - T(t-1) \tag{3}$$

Combining Equations (1) and (3), we get

$$Q(t) = Q(t-1) - T(t-1) + R(t-1) - R(t) + P(t-1), \tag{4}$$

which is the update equation of the departure queue.

III. Model structure

The three outputs of the model, $N(t)$, $Q(t)$ and $\tau(i)$, are related through the departure process. The departure process can be conceptually described in the following manner:

Aircraft pushback from their gates according to the pushback schedule. They enter the ramp and then the taxiway system, and taxi to the departure queue which is formed at the threshold of the departure runway(s). During this traveling phase, aircraft interact with each other. For example, aircraft queue to get access to a confined part of the ramp, to cross an active runway, to enter a taxiway segment in which another aircraft is taxiing, or they get redirected through longer routes to minimize interference with built up congestion. We cumulatively denote these spatially distributed queues and delays which occur while aircraft traverse the airport surface from their gates towards the departure queue as *ramp and taxiway interactions*. After the aircraft reach the departure queue, they line up to await takeoff. We model the departure process as a server, with the departure runways "serving" the departing aircraft in a First-Come-First-Serve (FCFS) manner. This conceptual model of the departure process is depicted in Figure 3.
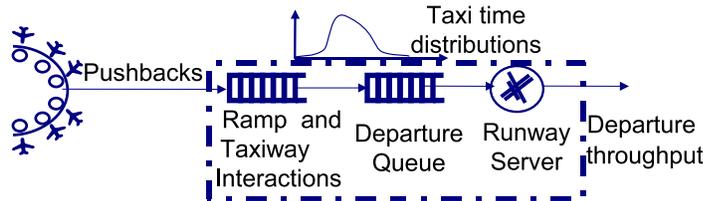
Figure 3: Integrated model of the departure process

By modeling the departure process in this manner, the taxi-out time τ of each departing aircraft can be expressed as

$$\tau = \tau_{unimped} + \tau_{taxiway} + \tau_{dep.queue} \tag{5}$$

The first term of Equation (5), $\tau_{unimped}$, reflects the nominal or *unimpeded taxi-out time* of the flight. This is the time that the aircraft would spend in the departure process if it were the only aircraft on the ground. The second term, $\tau_{taxiway}$, reflects the delay due to aircraft interactions on the ramp and the taxiways. In other words, $\tau_{taxiway}$ reflects the delay incurred due to other aircraft that are on their way to the departure queue. The number of such aircraft is given by $R(t) = N(t) - Q(t)$. The magnitude of this delay will depend on the exact interactions among the taxiing aircraft, or in other words, the level of congestion in the taxiways. The third term, $\tau_{dep.queue}$, is the time the aircraft spends in the departure queue. The duration of this time depends on the number of aircraft at the departure queue ($Q(t)$) and the runway service characteristics.

We observe that the taxi time of each departing aircraft depends on the model inputs and the two other model outputs ($N(t) - Q(t)$ and $Q(t)$). In contrast, the number of aircraft on the ground and in the departure queue, $N(t)$ and $Q(t)$ respectively, may be updated using Equations (3) and (4), as aircraft takeoff and pushback. Therefore, assuming that Equation 5 is an appropriate way to describe the departure process, the model may be built using the following steps:

1. Model $\tau_{unimped}$ as a function of the explanatory variables GL, RC and MC.
2. Model the dependence of $\tau_{taxiway}$ on $R(t)$, given RC and MC.
3. Model the statistical characteristics of the runway service process given RC and MC.

Then, given a pushback schedule and gate locations, we can use Equations (3-5) to get the outputs of the models.

In order to extract the dependencies mentioned above, we analyze a data set of observations from aircraft taxiing out at an airport. Combining the observed data with the explanatory variables, we can analytically describe $\tau_{unimped}$, $\tau_{taxiway}$ and $\tau_{dep.queue}$ and construct the required model.

IV. Data requirements

Ideally, we would like a dataset which consists of $\tau_{unimped}$, $\tau_{taxiway}$ and $\tau_{dep.queue}$, in order to study how these variables change with the model inputs. However, this information is not recorded. The recorded data that is publicly available for flights departing from an airport of study during a time period consists of:

1. Actual pushback time times
2. Actual takeoff times

   In addition to these, we can obtain the following information about the explanatory variables at each time-period:
3. Pushback schedules
4. Runway configuration
5. Reported meteorological conditions, and
6. Gate location for each departing flight

A. Data sources

The Aviation System Performance Metrics (ASPM) database offers a wealth of data which enables the study of the performance of the busiest 77 airports in the United States.[9] For every recorded flight, the ASPM database contains the fields (1-2) identified above. However, the airports we consider also serve a small number of flights that are not present in this dataset. These include some air taxi operations and military flights. We assume that this is a small number of flights that we can neglect.

Items 4 and 5 are obtained from the ASPM database,[9] where runway configurations and weather conditions are reported in 15-minute intervals. Gate location information (item 6) can be obtained from the airline assignment in some cases; for example, at BOS, the airline operating a flight is a sufficient proxy for the gate location information because there is no dominant airline and each major airline uses a spatially proximate and small (less than 20) set of gates.

V. Model development for BOS

In this section, we analyze how we can get estimates of the three terms of Equation (5), given a set of the explanatory variables (RC, MC, GL, PS) for Boston Logan International Airport (BOS). An inherent difficulty in the model calibration is the poor resolution of the available data: we do not have observations

of $\tau_{unimped}$, $\tau_{taxiway}$ and $\tau_{dep.queue}$, but instead only the actual pushback and takeoff times of flights. As a result, the calibration of the model makes several assumptions which are addressed in the next few sections. We also illustrate how these assumptions can be used for the calibration of the model for a particular runway configuration under VMC in BOS. The same procedure has also been utilized to calibrate the model for two other frequently used runway configurations under VMC in BOS.

A.   Unimpeded taxi-out times

The FAA defines the unimpeded taxi-out time as *the taxi-out time under optimal operating conditions, when neither congestion, weather nor other factors delay the aircraft during its movement from gate to takeoff*.[19] The following technique is used to estimate the unimpeded taxi-out time in the ASPM database:

First, the unimpeded taxi-out time is redefined in terms of available data as *the taxi-out time when the departure queue is equal to one[a] AND the arrival queue is equal to zero.* Then, a linear regression of the observed taxi-out times with the observed departure and arrival queues is conducted, and the unimpeded taxi-out time is estimated from this equation by setting the departure queue equal to 1 and arrival queue equal to 0.[10]

In the present work, we use the observations of Idris *et al.* that (1) there is poor correlation of the taxi-out times with arriving traffic, and (2) the taxi-out time of a flight $\tau(i)$ is more strongly correlated with its takeoff queue than the number of departing aircraft on the ground ($N(t)$).[12] We therefore redefine the unimpeded taxi-out time as the taxi-out time when the takeoff queue $N_Q(i)$ is equal to 0 (that is, when the number of takeoffs which take place between the pushback time of an aircraft and its takeoff time is equal to 0).

In Figure 4 we show the scatter (bubble) plot of $\tau(i)$ vs. $N_Q(i)$ in BOS for all runway configurations under all meteorological conditions, as well as the linear regression fit. The size of each bubble is proportional to the frequency with which that point is observed.

The bubble plot indicates that the linear regression may not be appropriate for getting a good estimate of the unimpeded taxi-out time, since the line is significantly below the majority of the observations for low values of $N_Q(i)$. While the linear regression gives a fairly good fit for much of the data ($R^2 = 0.538$), it is not a good approximation for the regime that we are interested in, namely, for low values of takeoff queue length. The ASPM database corrects for this effect by excluding the highest 25 percent of the values of actual taxi-out time from the regression while estimating the unimpeded taxi-out times. This step is taken to "remove the influence of extremely large taxi-out times from the estimation of expected taxi time under optimal operating conditions".[10] This is, however, an empirical metric, and does not explain why the 75th is an appropriate percentile of flights to use (in order to exclude congestion effects), or why the bias that the flights under medium-traffic conditions introduce in the estimation is not important. Figure 4 suggests that a piecewise linear regression might be more appropriate. In that case, the first line-segment could be used to estimate the unimpeded taxi time. However, there is no clear choice of the number of the segments in a piecewise regression.

We know that by definition, unimpeded taxi times are observed when neither congestion nor other extraneous factors delay the aircraft during its movement from gate to takeoff. Therefore, we need to restrict our analysis to small values of $N_Q(i)$. Unfortunately, this renders the population size of our sample small, and we cannot ensure that the statistical significance of the other factors is negligible. We also need to address the practical problem of choosing the critical value of $N_Q(i)$ below which it is regarded as "small". In the following discussion, we propose a new method for systematically inferring the unimpeded taxi-out times.

Let us assume that the taxi-out time is of the form

$$\tau(i) = p_o + p_1 N_Q(i) + W(i), \tag{6}$$

where $W_1, \cdots, W_n$ are independent identically distributed (i.i.d.) normal random variables with mean zero and variance σ^2. Then, given $N_Q(i)$ and the realized values of $\tau(i)$, the Maximum Likelihood estimates of the parameters p_0 and p_1 can be calculated using standard linear regression formulas.

We begin the linear regression $\tau(i)$ vs. $N_Q(i)$ by keeping $N_Q(i) \leq 4$. We use Student's t-test to evaluate whether the estimates of p_1 thus obtained have statistical significance. If not, we increment the limit of

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[a]ASPM defines the departure queue as the number of aircraft on the ground, so it is equivalent to $N(t)$, as defined in Section II
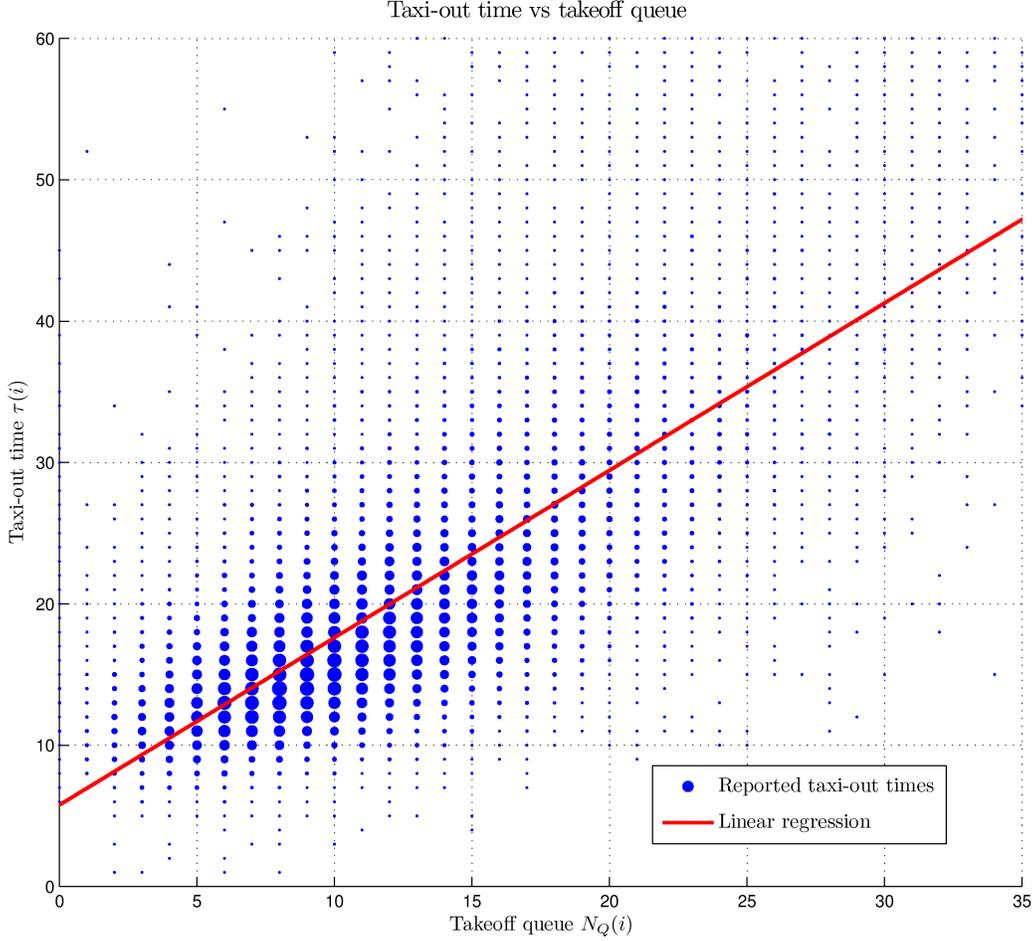
Figure 4: $\tau(i)$ vs. $N_Q(i)$ scatter

$N_Q(i)$ (below which flights are included in the regression analysis) by 1 until we obtain a significantly positive estimate of p_1, and a significantly positive estimate of p_0. We denote this limit N_U. The unimpeded taxi time is then given by

$$\tau_{unimped} = p_o \tag{7}$$

and its variance is given by its unbiased estimator:[2]

$$\hat{S_n}^2 = \frac{1}{(n-2)} \sum (\tau(i) - p_o + p_1 N_Q(i))^2. \tag{8}$$

This regression analysis is conducted for each segment (RC, MC) and for each "gate location" in BOS, with the operating airline of a flight serving as a surrogate for the "gate location". In other words, for each airline operating in BOS, we calculate the expected unimpeded taxi-out time. We illustrate this process in the next section with an example.

1. *Example of unimpeded taxi-out time calculation*

Figure 5 shows the bubble plot of the taxi-out times $\tau(i)$ of Comair (COM) vs. $N_Q(i)$ when configuration 4L, 4R | 4L, 4R, 9 is in use at BOS under VMC. We also depict the linear regression across all data, which lies below the majority of the observed taxi-times for low values of $N_Q(i)$, as was the case when we considered all flights (Figure 4).

If we apply the above described methodology to estimate the unimpeded taxi-out time of Comair when configuration 4L, 4R | 4L, 4R, 9 under VMC is in use, we find that the smallest $N_Q(i)$ which provides

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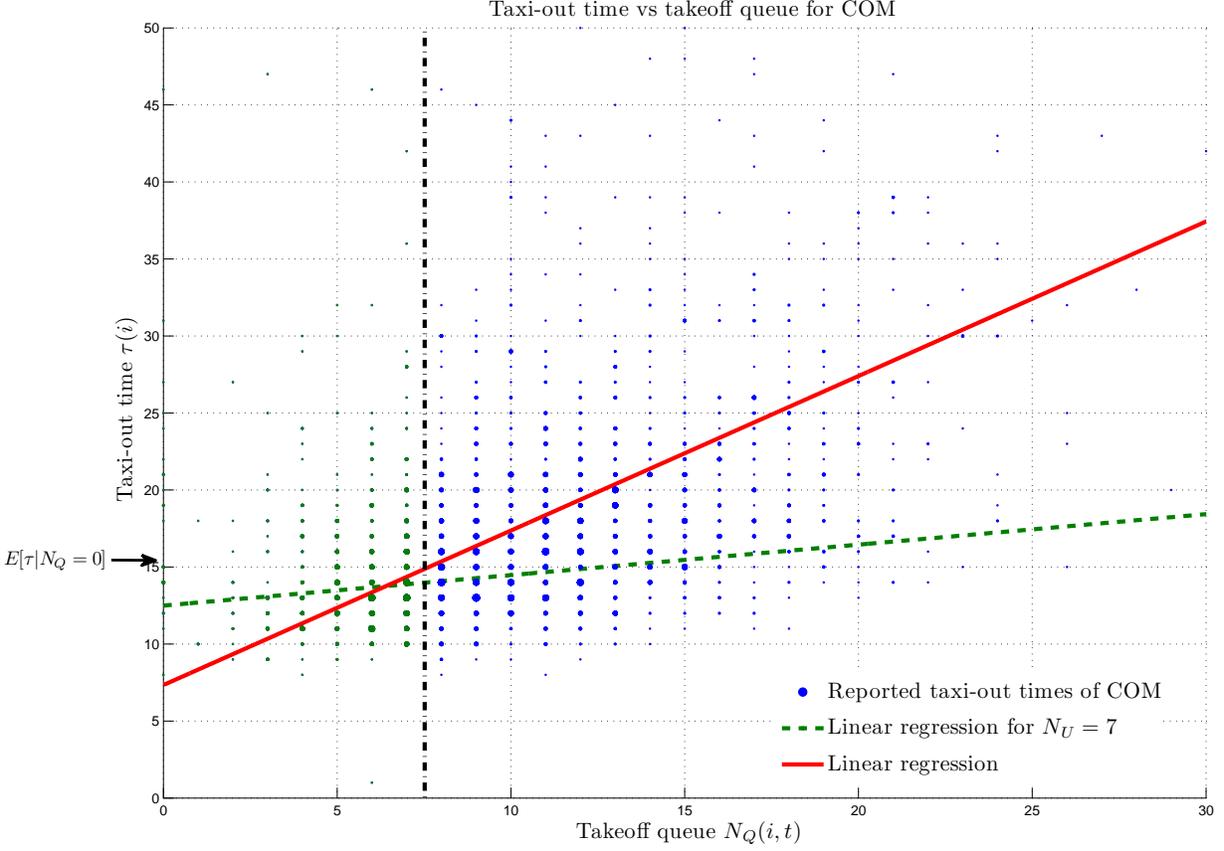
Figure 5: $\tau(i)$ vs. $N_Q(i)$ scatter for Comair

estimates that have statistical significance is $N_U = 7$. When we apply linear regression for $\tau(i)$ vs. $N_Q(i)$ while keeping $N_Q(i) \leq 7$, we have a total of 491 observations, and applying Equations 7 and 8 we estimate the unimpeded taxi-out time of Comair to be given by a normal random variable $\mathcal{N}(12.45, 3.03)$. Had we applied the linear regression to the whole dataset, we would have gotten as an estimate of the unimpeded taxi-out time the value of 7.34 minutes. If, on the other hand, we had inferred the unimpeded taxi time as the average observed taxi time of Comair when a Comair aircraft was the sole aircraft on the ground ($N_Q(i) = 0$), we would have estimated the unimpeded taxi time to be 15.27 minutes. This large deviation occurs because there are only 11 observations for $N_Q(i) = 0$, and an estimate based solely on them is likely to be prone to error. The choice of N_U is essentially a compromise between the need for having a sufficient number of observations to obtain a statistically significant estimate, and the need to not include observations corresponding to high values of $N_Q(i)$ will bias the estimate. A final observation that can be made by comparing the two regression fits in Figure 5 is that the red line (corresponding to the linear regression on all observations) has a steeper slope than the (almost flat) blue line (corresponding to observations with $N_Q(i) \leq 7$). This is to be expected since in the low congestion regime (low values of $N_Q(i)$), the marginal delay cost of adding one more aircraft in the takeoff queue is smaller than the average value over all congestion levels.

ASPM provides four seasonal estimates for the unimpeded taxi-out times of Comair in Boston, the average of which is 16.85 min. However, ASPM does not differentiate between different runway configurations, or weather conditions. Several authors[13, 20] have already noted the dependence of the unimpeded taxi time on the runway configuration and we have also verified this observation in our analysis. This observation can be explained intuitively since the unimpeded time is the nominal time an aircraft needs to travel from point A (its gate) to point B (the runway), and will depend on the location of point B (the runway assignment). A possible approach to adapt the ASPM analysis method on a particular runway configuration is the following:

- Obtain the scatter plot of the taxi time $\tau(i)$ vs. the number of aircraft on the ground $N(t)$ for a given runway configuration

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- Apply the truncated linear regression to the above data omitting the highest 25 percent of the observed taxi times (that is, using 75 percentile of the data)

- The unimpeded taxi time can then be determined by the intercept of the linear regression fit with the y-axis[b].

In figure 6, we illustrate this process. We also show the highest 25% of the taxi times and the linear regression fit using all taxi times vs. $N(t)$.
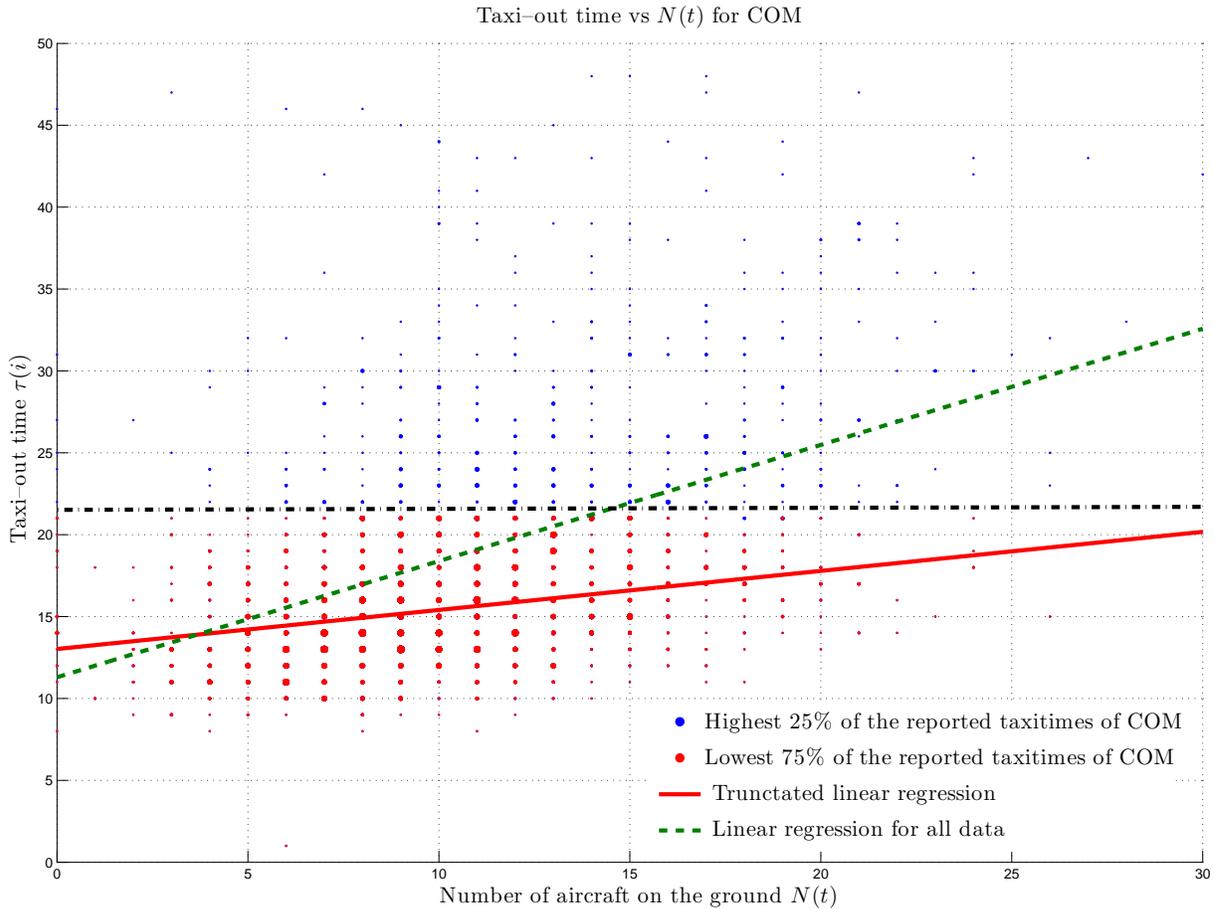
Figure 6: $\tau(i)$ vs. $N(t)$ scatter for Comair

The following observations can be made regarding Figures 5 and 6:

- The data in Figure 5 exhibit a more narrow scatter than the data in Figure 6. In addition, the R^2 value in the latter case is only 0.10 compared to 0.51 in the former. This is consistent with the conclusion of Idris *et al.* that the taxi-out time $\tau(i)$ of a flight is more strongly correlated with its takeoff queue than with the number of departing aircraft on the ground.[12]

- Excluding the highest 25% of the reported taxi times partially corrects for the bias that is introduced by including observations corresponding to large values of $N(t)$. However, there is no clear justification for choosing the highest 25% of the reported taxi times, and in addition, we find that the number of aircraft on the ground, $N(t)$, is a poor predictor the expected taxi-out time, especially when compared to the length of the takeoff queue, $N_Q(i)$.

- The line of the linear regression using all data in Figure 5 has a steeper slope than the corresponding one in Figure 6 (a value of 1.1 compared to 0.7). This implies that the incremental delay cost incurred

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[b]According to the definitions we gave in Section II, $N(t) = 0$ when an aircraft pushes back and is the sole departing aircraft on the surface of the airport

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by a flight i from adding one more flight in its takeoff queue, that is, to $N_Q(i)$, is higher than that from adding one more departing flight on the surface (i.e., to $N(t)$). This is due to the fact that there is a non-zero probability that the additional aircraft on the surface will be behind the aircraft i or will be overtaken by it in the taxiing process,[12] and that it will not be in the takeoff queue of flight i.

B.   Identification of throughput saturation points

In order to determine the amount of time that each aircraft will spend waiting in the departure queue, we need to first determine the statistical characteristics of the runway departure process. This can be done through the observation of runway performance under heavy loading. Under such conditions runways operate at their capacity, and by observing the output of the process the statistical properties of the server (the runways) may be inferred.[20] However, the regimes in which the runway process is saturated and the runway operates at capacity need to first be identified.

Following the approach proposed by Pujet,[20] we use the number of departing aircraft on the ground as an indicator of the loading of the departure runway. We define $\bar{T}_n(t + dt)$ as the takeoff rate over the time periods $(t + dt - n, t + dt - n + 1, ..., t + dt, ...t + dt + n)$. The maximum correlation between $N(t)$ and $\bar{T}_n(t + dt)$ is obtained for $n = 10$ and $dt = 10$ for BOS, for the high-throughput configurations used under VMC conditions. This means that the number of departures on the surface at time t, namely $N(t)$, is a good predictor of the number of takeoffs during the time interval $(t, t + 1, t + 2, \cdots, t + 20)^c$.

As $N(t)$ increases, the takeoff rate initially increases, but saturates at a critical value N^*. The existence of N^* can be explained as follows: initially, as the number of aircraft on the surface increases, so does the number of departing aircraft. Beyond this threshold value of N, the runway becomes the defining capacity constraint, and increasing the number of aircraft further does not increase the throughput of the airport. This is consistent with the findings of prior studies.[20, 22] Applying similar techniques to BOS data for the year 2007, we determine the following *saturation points* for the most frequently used runway configurations in BOS under VMC conditions (Table 3).

Table 3: Runway saturation points for most frequent configurations used in BOS

Configuration	N^*
22L, 27 | 22L, 22R	16
4L, 4R | 4L, 4R, 9	17
27, 32 | 33L	21

Figure 7 shows the average takeoff rate as a function of $N(t)$ for the segment (4L, 4R \| 4L, 4R, 9; VMC) in BOS. The saturation point is also denoted. We note that the takeoff rate initially increases as $N(t)$ increases, but subsequently saturates at about 0.73 aircraft/min or 44 aircraft/hour. This number can be viewed as the sustained departure capacity of BOS for the segment.

C.   Modeling the runway service process

Having identified the regime of operations when the runway loading is high, it is possible to model the runway departure process itself. One possible approach (adopted by Pujet[20]) is to observe the takeoff rate $\bar{T}_n(t+dt)$ when $N(t)$ is larger than N^*, and to then model the runway capacity as a binomial random variable with the same mean and variance as the observed $\bar{T}_n(t + dt)$. While this is convenient for mesoscopic modeling, this approach does not try to reflect the characteristics of the runway, but instead reproduces the first and second order moments of the training data (a year of operations). Some of the inherent problems of the above modeling approach (pertaining to runway performance in particular) were noted by Carr.[5]

In this study, we propose an alternate approach to modeling the runway service process. Let us examine the inter-departure times of the aircraft configurations: 4L, 4R \| 4L, 4R, 9 at BOS during high loads $(N(t) > 17)$. We use this data to construct a histogram of inter-departure times, as shown in Figure 8 (left). From this histogram, we find the mean inter-departure time to be 1.3 minutes with a standard deviation of

---

[c]In a prior study, Pujet estimated that $(n, dt) = (5, 6)$.[20] This difference can be explained by the observation that his data included only 65% of flights and because both traffic and reporting rates at BOS have risen significantly over the past 10 years.
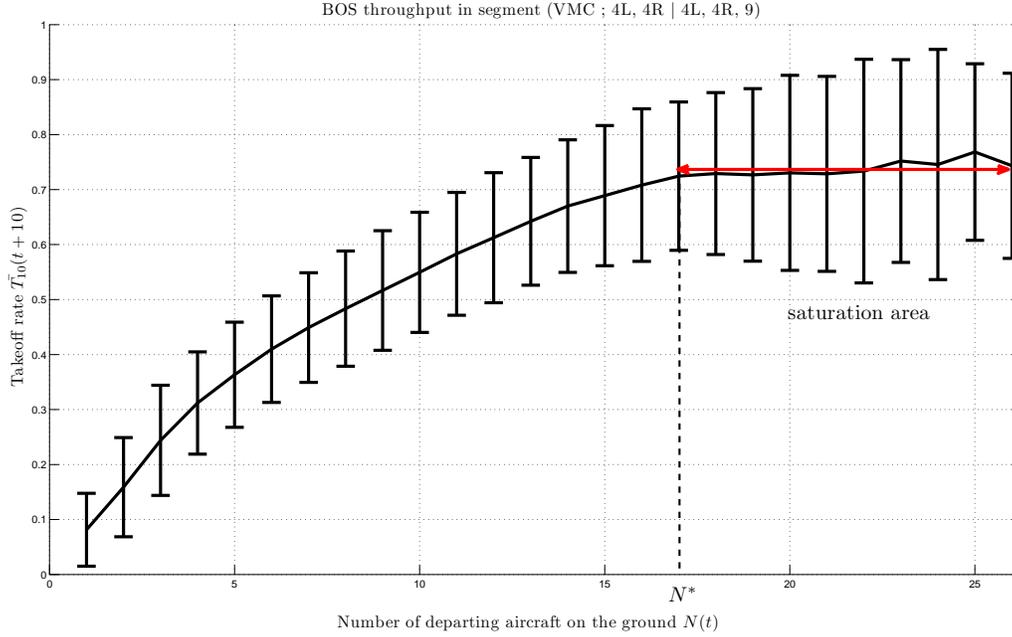
Figure 7: Takeoff rate as function of $N(t)$

0.9 minutes. Another noteworthy observation is that 75% of the departures are separated by two minutes or less.

The distribution (during congested operations) reflects a combination of endogenous factors such as the departure process (availability of more than one departure runway; ATC wake vortex separation), and exogenous factors such as communication delays or interactions with arriving traffic. Ideally, one would like to factor in all these parameters in the model. However, for the sake of simplicity, we model the departure process probabilistically in the following manner:

We assume that the service time of each aircraft is random variable of the event "departure" that has three possible outcomes. The first two possible outcomes are one and two minutes. This is consistent with the fact that the typical runway occupancy time for commercial air carriers is approximately a minute. In addition, looking at all of the airports we have considered including this particular segment of BOS, the vast majority of the inter-departure times are within two minutes. Lastly, the third outcome is the next minute increment that satisfies the conditions:

- All three outcomes have positive probabilities
- The sum of the probabilities is 1
- the resulting probability mass function (PMF) has equal first two moments to the observed one

In this particular segment, this event is the 5-min service time. The original histogram and the resulting PMF used in the model can be seen in figure 8.

In this way we account for the probabilistic nature of the runway service process, but model it in a simple way. Given an estimate of the times at which departing aircraft reach the runway, we can use this model of runway operations to predict the amount of time that each flight will spend waiting in the runway queue (denoted $\tau_{dep.queue}$).

D. Modeling ramp and taxiway interactions

The remaining unmodeled term in Equation (5), namely $\tau_{taxiway}$, represents the effect of queuing in the ramp area and the taxiways. This term is the most difficult to estimate, since there are no distinct operating conditions in which it is the dominant term. As a first step, we neglect this term. In other words, we assume
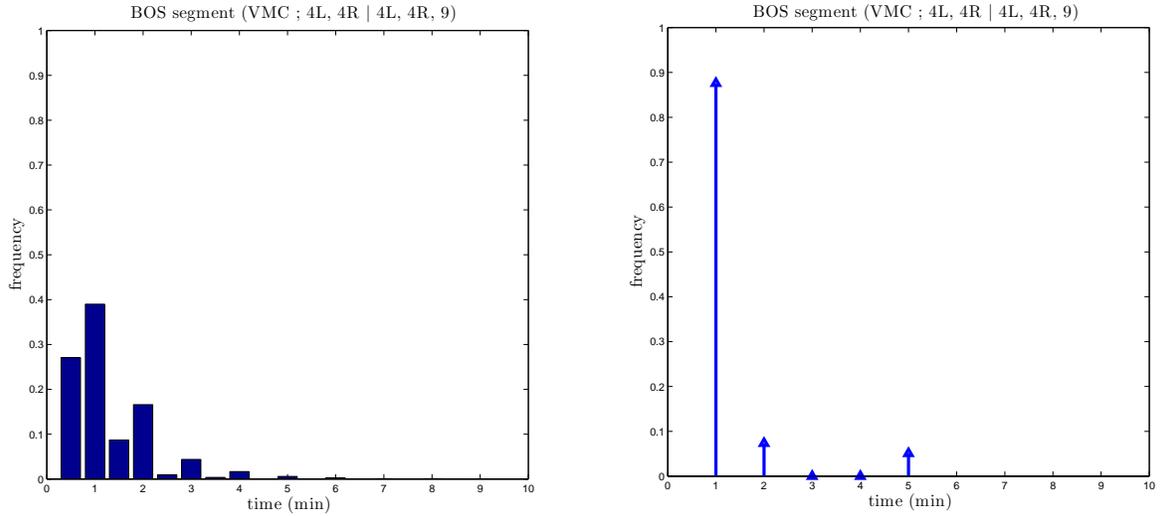
Figure 8: [Left] Histogram of inter-departure times; [Right] Simplified histogram of inter-departure times.

that aircraft travel for their unimpeded taxi-out times and then reach the runway queue where they are processed according to the probabilistic process described in the previous section.

We test this model on the departure schedule from BOS in 2007 for the time intervals when the runway configuration 4L, 4R | 4L, 4R, 9 was used under VMC conditions. We only consider time intervals that the segment was in use consecutively for longer than four hours so as to immune the performance of the model from transitional effects that are out of the scope of this model. Figure 9 compares the performance of the model with the observed data.
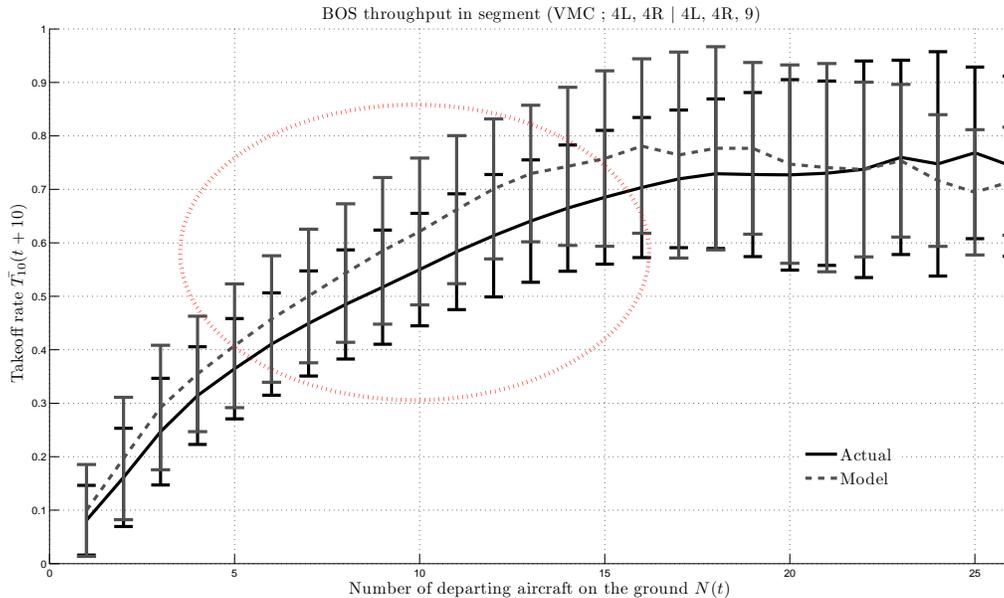
Figure 9: Actual and modeled takeoff rate as a function of $N(t)$, when taxiway interactions are neglected.

We observe that the performance of the model deteriorates at medium traffic conditions. This behavior may be explained through a closer look at the model: aircraft are assumed to reach the runway queue within their unimpeded taxi-out times, which are realized in light traffic conditions. Therefore, neglecting taxiway interactions is a reasonable approximation in low traffic. In heavy traffic conditions, the runway is saturated and the takeoff queue is expected to be long, so the runway queue time is the dominant factor in predicting the total taxi time. However, at medium traffic conditions, the assumption that aircraft always travel their

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nominal taxi time leads to predictions that are more optimistic than in real operations, as seen in Figure 9. This is because the model predicts that aircraft reach the runways at a higher rate than in reality (since the model assumes that they only taxi for their unimpeded times), and do not wait at the runway (since the runway queues are not saturated). This issue can also be seen in Figure 10, which depicts the frequency that different congestion states are observed in reality and in the model: The model predicts the airport being at low congestion levels much more often than observed. This happens because the predicted takeoff rates tend to be greater than the observed rates. We hypothesize that this happens because of neglecting $\tau_{taxiway}$ and that the performance of the model can be improved by including this term.

In addition, accounting for taxiway congestion effects allows us to obtain better estimates of the number of aircraft in the taxiway system ($R(t)$) and in the runway queue ($Q(t)$). In particular, a good estimate of $Q(t)$ will also help in the departure planning process.
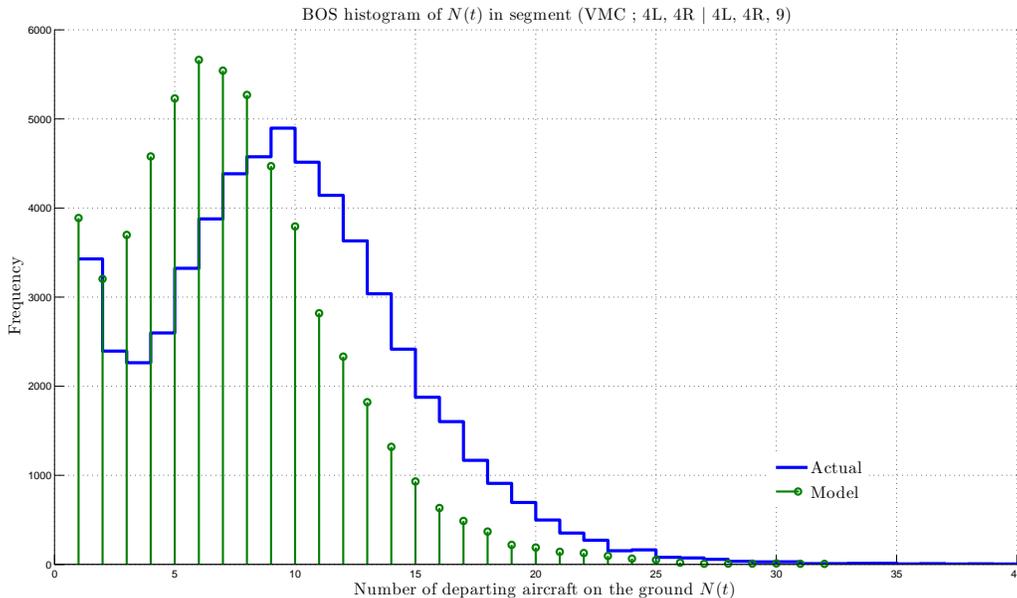
Figure 10: Actual and modeled $N(t)$ histogram, when taxiway interactions are neglected.

We now refine our model by relaxing the assumption that the aircraft take just their unimpeded taxi-out time to reach the runway. Equation (5) is modified so that the travel time of an aircraft from its gate to the runway queue depends on its unimpeded taxi-out time and on the amount of traffic on the ramps and the taxiway at the time. The modified equation becomes

$$\tau = \tau_{travel} + \alpha R(t) + \tau_{dep.queue} \tag{9}$$

The term $\alpha R(t)$ is a linear term used to model the interactions among departing aircraft on the ramps and taxiways. α is a parameter that depends on the airport and the runway configuration. Its value can be chosen so as to yield the optimal fit between the actual and the modeled distributions. There are four quantities that are critical to the performance of the model, namely, the plot of $\bar{T}_n(t+dt)$ vs. $N(t)$, the histogram of N, the distribution of τ vs. N, and the histogram of τ.

Since α is the only parameter in our control,we would like to choose α so as to get optimal fit between the modeled and the actual statistics for the above quantities. We decide to choose α so as to get the optimal fit between the distributions of observed and modeled $N(t)$. This is based on the following argument:

For all different values of α we try, we obtain different distributions of $N(t)$. The one that has the optimal fit to the observed $N(t)$ will also predict optimally the take-off rate. As we have shown in equation (3), $N(t)$ is updated in the following manner: $N(t) = N(t-1) + P(t-1) - T(t-1)$. The pushback schedule is fixed and the same for all different values of α that we try. The only way to make a transition from $N = 0$ to $N = 1$ is through a pushback. So, this transition is the same for all values of α. All other transitions are a function of pushbacks,which are fixed, and takeoffs, which are predicted by the model. Thus, the optimal fit between the observed and modeled $N(t)$ will ensure the optimal prediction of the take-off rate across the different states of surface traffic.

A good estimate of the histogram of N also has the added benefit of yielding good estimates of taxi time metrics. If this were not the case, taxi times would tend to be lower or higher in the model than they are in reality. That would, in turn, lead to a bad fit between the actual and the observed histogram of N: If the estimated taxi times were smaller, then modeled N frequencies would be higher than the actual and the high values of N would be under-represented. If the estimated taxi times were larger, then modeled N frequencies would be lower than the actual and the high values of N would be over-represented.

To summarize, choosing α to find the best fit between the distributions of observed and modeled N will optimize the overall performance of the model. We choose the Pearson's χ^2-test statistic to measure the fit:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{10}$$

where $\chi^2 =$ the test statistic; $O_i =$ the modeled frequency of the congestion state i; $E_i =$ the actual frequency of the congestion state i; $n =$ the number of different congestion states observed.

For the most frequently used segments in BOS, the optimal values of α are given in Table 4. We run the

Table 4: Parameter α for different BOS runway configurations

Segment	α
(VMC; 22L, 27 | 22L, 22R)	0.44
(VMC; 4L, 4R | 4L, 4R, 9)	0.54
(VMC; 7, 32 | 33L)	0.56

model again using Equation 9 for configuration 4L, 4R | 4L, 4R, 9 under VMC conditions. A comparison of Figures 9 and 11, and Figures 10 and 12, illustrate the benefits of including the taxiway interaction term in the expression for taxi-out time.
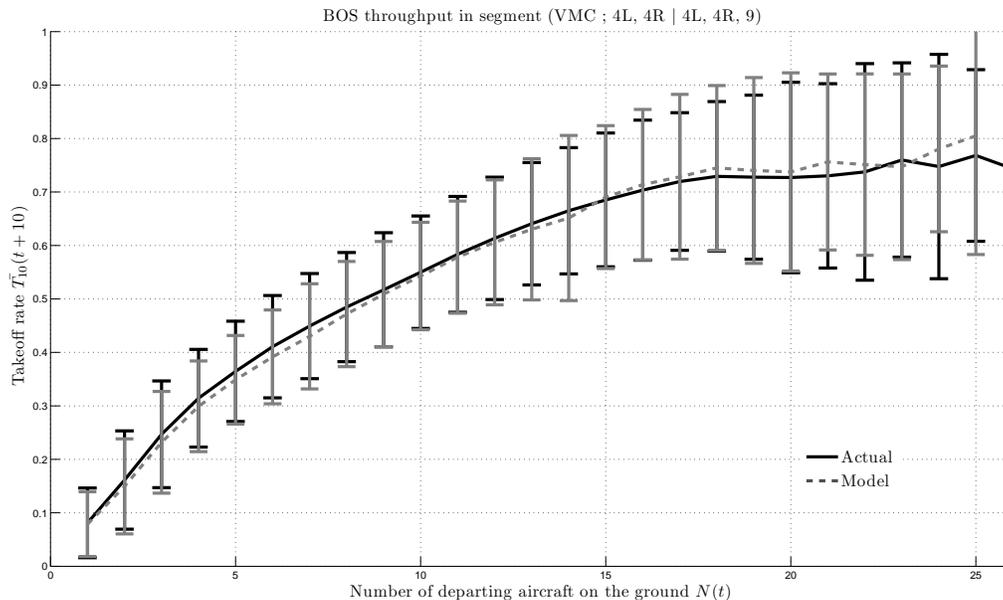
Figure 11: Actual and modeled takeoff rate as a function of $N(t)$, when taxiway interactions are included.

VI.   Model results

Table 5 lists the three most frequently used segments in BOS and the number of flights that were observed to both pushback and take-off in each segment when the segments were consecutively used for four hours or longer. The reason we test the model for periods of use to that are not shorter than four hours and only for flights that pushed back and took off in a particular segment is for minimizing the effects of configuration or

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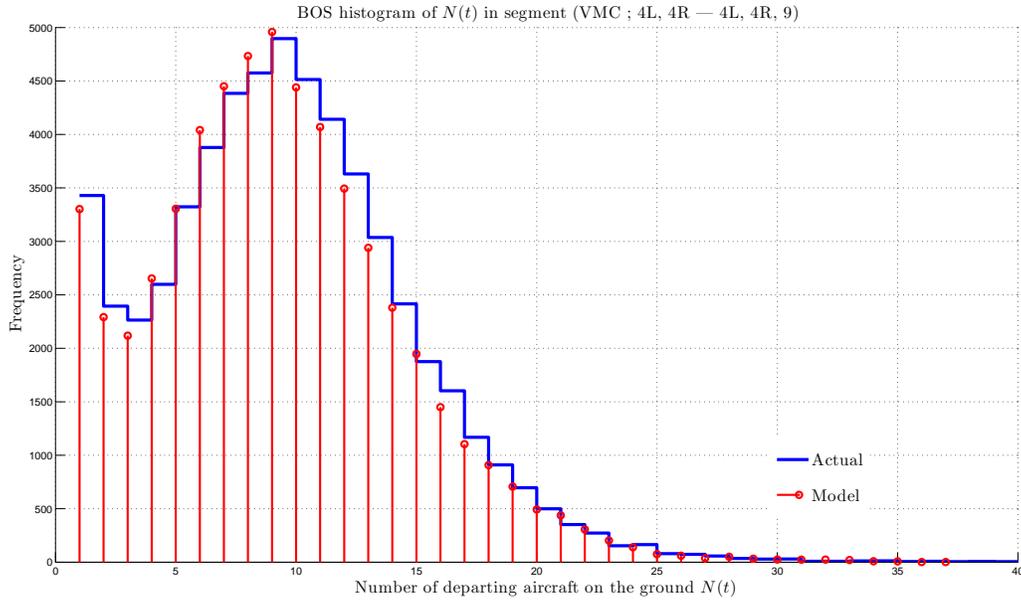
Figure 12: Distributions of observed and modeled $N(t)$

weather change events when measuring the performance of the model. Table 5 also lists the actual and the modeled mean taxi time for each segment, and Tables 6-8 contain more detailed statistics about the number of aircraft and the taxi times in different congestion levels. These statistics were obtained from the average values of running the model 10 times.

Table 5: Actual and modeled taxi times for different BOS segments

Segment	Hrs in use	Flights	Actual avg. taxi time	Modeled avg. taxi time
(VMC; 22L, 27 | 22L, 22R)	2,077	40,009	20.25	20.29
(VMC; 4L, 4R | 4L, 4R, 9)	1,190.5	27,306	18.63	18.59
(VMC; 7, 32 | 33L)	954	20401	21.36	21.51

Table 6: Model predictions for segment (VMC; 22L, 27 \| 22L, 22R)

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	14,253	16.43	13,792	16.42
($9 < N \leq 16$)	19,856	20.62	20,703	20.48
($N \geq 17$)	5,900	28.24	5,514	29.03

Table 7: Model predictions for segment (VMC; 4L, 4R \| 4L, 4R, 9)

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	10,884	15.88	10,948	15.60
($9 < N \leq 16$)	13,841	19.46	13,805	19.50
($N \geq 17$)	2,481	25.96	2,553	26.74

Table 8: Model predictions for segment (VMC; 7, 32 \| 33L)

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	6,298	17.43	5,732	17.79
($9 < N \leq 16$)	10,728	21.58	11,707	21.66
($N \geq 17$)	3,375	27.94	2,962	28.40

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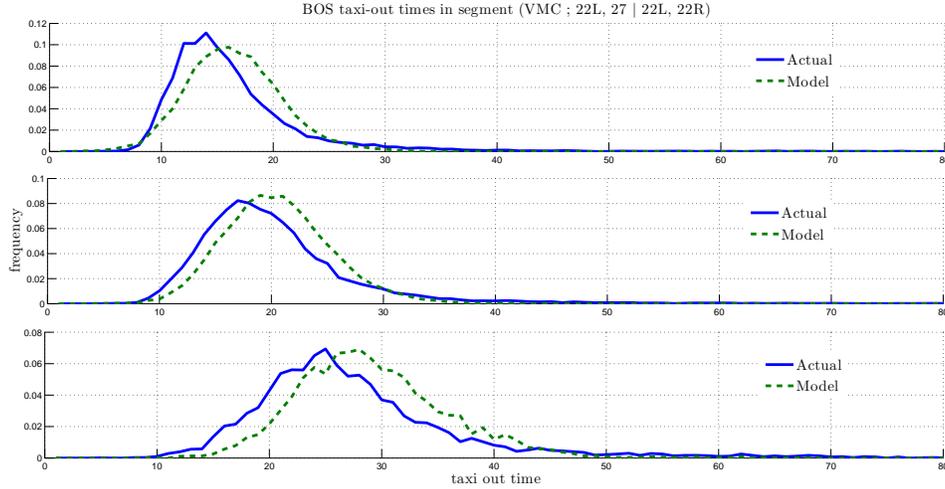
Figure 13: Taxi-out time distributions under low ($N \leq 8$), medium ($9 < N \leq 16$) and heavy ($N > 17$) departure traffic on the surface for configuration 27, 32 | 33L.
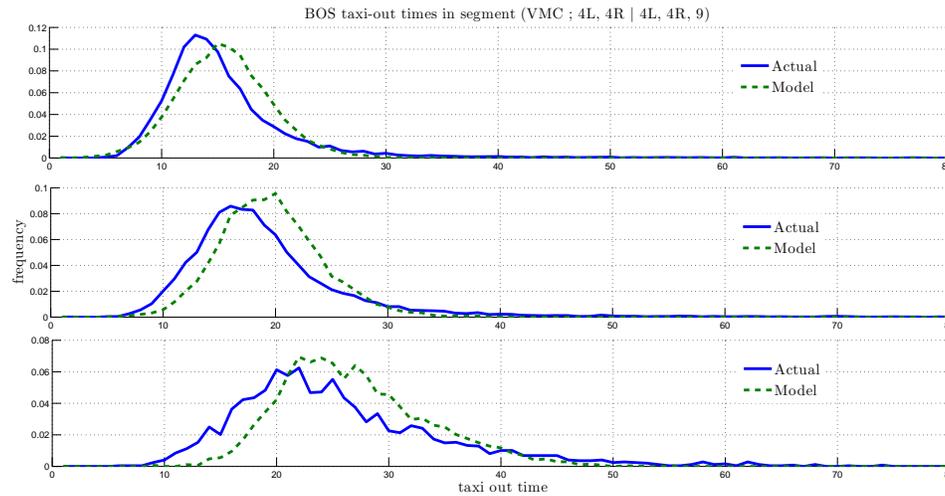
Figure 14: Taxi-out time distributions under low ($N \leq 8$), medium ($9 < N \leq 16$) and heavy ($N > 17$) departure traffic on the surface for configuration 4L, 4R | 4L, 4R, 9.

In addition, the typical taxi time distributions predicted and observed over different ranges of $N(t)$ can also be analyzed. The actual taxi time distributions and an instance of the ones provided by a random model run are shown in Figures 13, 14 and 15 for the three most frequently used segments.

A. Predicting runway queues and taxiway congestion

It is possible to use Equation (9) with the identified parameters to predict the amount of time an aircraft will spend taxiing on the taxiway and the amount of time in the runway queue. An example is shown for a particular configuration at BOS, in Figure 16. We note that as congestion increases, an aircraft can spend more than half of its total taxi time in the runway queue. This demonstrates the potential for reducing emissions by controlling the length of the runway queue.

VII.   Model Validation

The model parameters in the previous sections were identified using BOS operations data from 2007. We validate this model using data from 2008. We evaluate the performance of the model in terms of throughput

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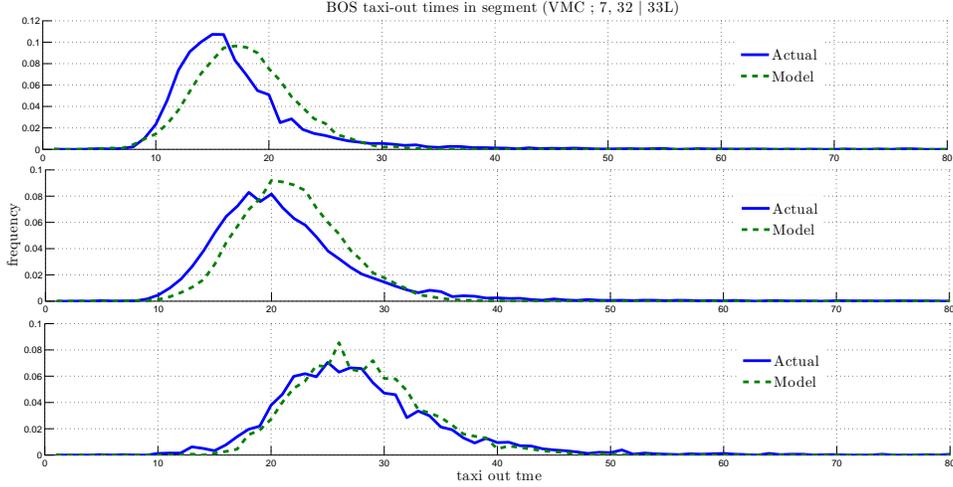
Figure 15: Taxi-out time distributions under low ($N \leq 8$), medium ($9 < N \leq 16$) and heavy ($N > 17$) departure traffic on the surface for configuration 22L, 27 | 22L, 22R.
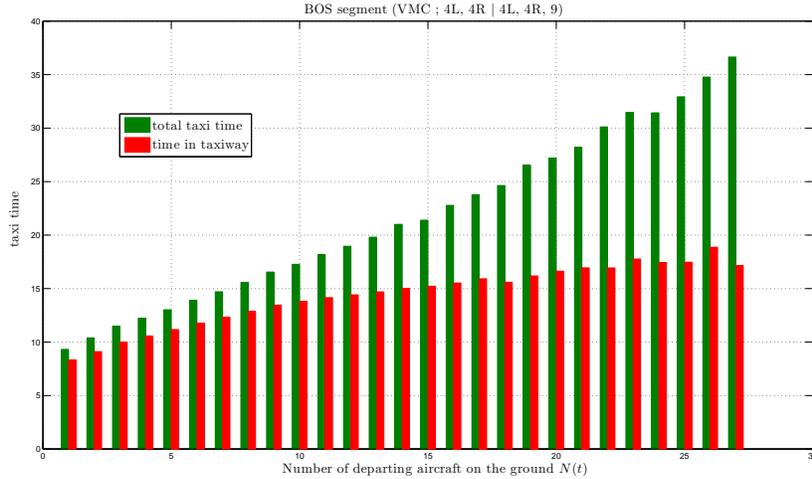
Figure 16: Estimated time spent by an aircraft transiting the taxiways and waiting in the runway queue for different levels of surface traffic.

predictions, the frequencies of the predicted and observed values of $N(t)$, and the distributions of actual and observed taxi times. The validation process consists of:

1. Using the model with the parameters calculated in Section V for different configurations and weather conditions (runway capacity model, α and τ_{travel} identified using 2007 data) to simulate operations with the reported pushback times during 2008.

2. Comparing the simulation results with the reported departure throughput and taxi-out times for 2008.

Similar to Table 5, Table 9 lists the three most frequently used segments in BOS and the number of flight that were observed to both pushback and take-off in each segment when the segments were consecutively used for four hours or longer. Table 9 also lists the actual and the modeled mean taxi time for each segment. Tables 10 to 12 contain more detailed statistics about the number of aircraft and the taxi times in different congestion levels. The statistics of the model predictions in Table 9 and in Tables 10 to 12 were obtained from the average values of running the model 10 times.

We observe that, with the exception of the segment (VMC; 4L, 4R | 4L, 4R, 9), the model predicts 2008 taxi times very accurately and there is no apparent difference in the performance of the model against the training (2007) and the test data set (2008). Comparing Figures 13 and 17 further shows that the model

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predicts 2008 taxi times as well as it fits the 2007 data. Figure 18 shows the observed and predicted takeoff rate for this segment in 2008.

Table 9: Actual and modeled taxi times for different BOS segments in 2008

Segment	Hrs in use	Flights	Actual avg. taxi time	Modeled avg. taxi time
(VMC; 22L, 27 | 22L, 22R)	1,805	32,895	19.79	19.63
(VMC; 4L, 4R | 4L, 4R, 9)	1,136.5	23,978	17.30	18.45
(VMC; 7, 32 | 33L)	894.25	20401	21.51	21.19

Table 10: Model predictions for segment (VMC; 22L, 27 \| 22L, 22R) for 2008

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	13,362	16.81	13,436	16.51
($9 < N \leq 16$)	16,008	20.68	16,271	20.49
($N \geq 17$)	3,525	28.24	3,188	28.44

Table 11: Model predictions for segment (VMC; 4L, 4R \| 4L, 4R, 9) for 2008

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	11,271	15.45	10,235	15.52
($9 < N \leq 16$)	11,447	18.39	11,715	19.70
($N \geq 17$)	1,230	23.96	2,028	26.00

Table 12: Model predictions for segment (VMC; 7, 32 \| 33L) for 2008

Congestion level	Act. # of flights	Act. avg. taxi time	Modeled # of flights	Modeled avg. taxi time
($N \leq 8$)	6,199	17.58	6,187	17.81
($9 < N \leq 16$)	8,960	21.94	9,512	21.78
($N \geq 17$)	2,766	28.91	2,224	28.02

VIII. Management of the pushback queue

The data analysis confirms prior observations[20, 22] that there is a strong correlation between the number of the aircraft on the ground and the departure throughput, and that there is a critical number of aircraft on the ground N^* at which the departure process gets saturated. In other words, increasing the number of the aircraft on the ground any further does not increase the departure throughput. The estimated values of N^* for different runway configurations at BOS are listed in Table 3.

We would like to use N^* as listed in table 3 for taxiing operations control. This approach had been considered previously in the Departure Planner[11] and variants of it have been extensively studied.[3, 6, 21] We use the models developed in this paper to evaluate in detail the potential benefits of the strategy initially studied by Pujet *et al.*[20]The proposed algorithm can be thought of as *virtual departure queuing* and is often referred to as *N-Control*.[4, 6] It can be summarized as follows: At each time period t,

- If $N(t) \leq N^*$,

  - If the *virtual departure queue* (set of aircraft that have requested clearance to pushback) is not empty, clear aircraft in the queue for pushback in FCFS order

- If $N(t) > N^*$, for any aircraft that requests pushback,

  - If there is another aircraft waiting to use the gate, clear departure for pushback, in FCFS order
  - Else add the aircraft to the *virtual departure queue*.
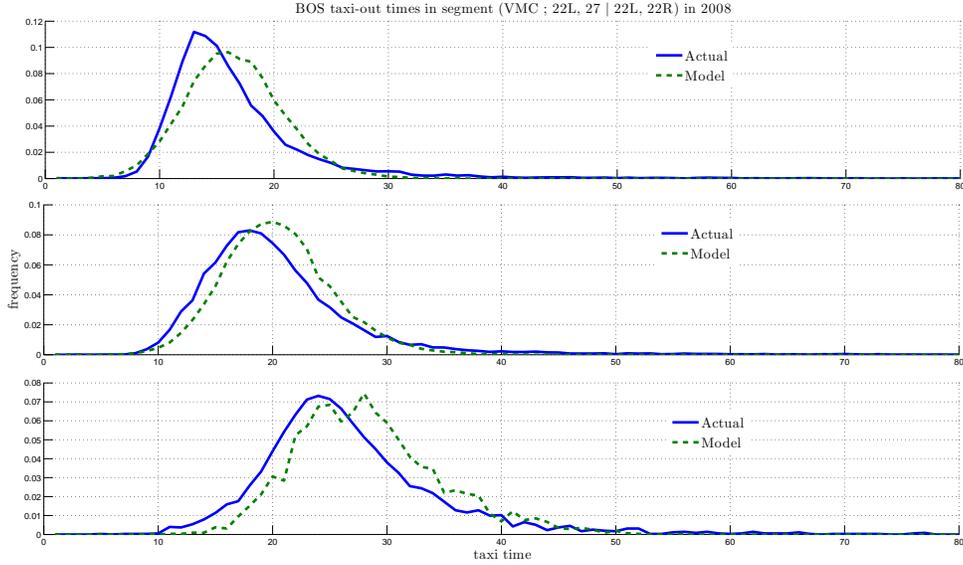
Figure 17: Taxi-out time distributions under low ($N \leq 8$), medium ($9 < N \leq 16$) and heavy ($N \geq= 17$) surface traffic for configuration 22L, 27 | 22L, 22R in BOS in 2008.
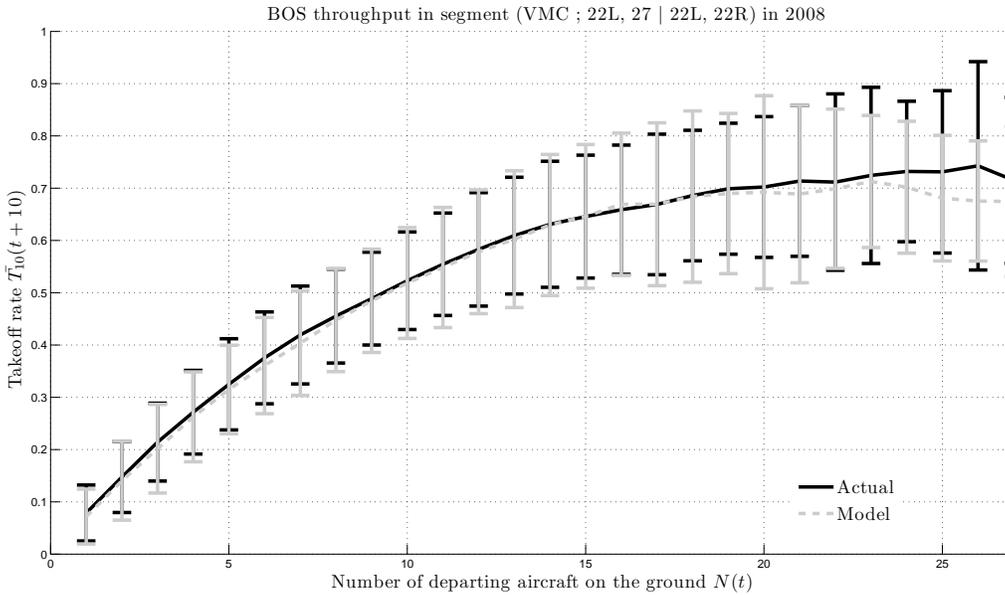
Figure 18: Takeoff rate $\bar{T}_9(t+9)$ as a function of $N(t)$ for configuration 22L, 27 | 22L, 22R in BOS in 2008. The model was derived from a training set of data from 2007.

In other words, when $N(t) > N^*$, we regulate the pushback time of an aircraft unless it may delay an arrival that is waiting to use the gate. In order to maintain fairness, aircraft which request pushback clearance and are not cleared immediately form a FCFS-*virtual departure queue*. When the congestion decreases and $N(t) \leq N^*$, we allow the aircraft in the virtual departure queue to pushback in the order that they requested pushback clearance. This approach enables reductions in fuel burn and emissions, without decreasing the departure throughput. A schematic of the controlled departure process is shown in Figure 19.

Finally, it may be the case that the initial estimate of N^* leads to gate holds or delays longer than airlines are willing to accept, or that some airport authority wants to exercise more aggressive emissions control.

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Therefore, we allow the critical number of aircraft at which the aircraft are held in the *virtual departure queue* to take different values in the simulations. We denote this value as N_{ctrl}.
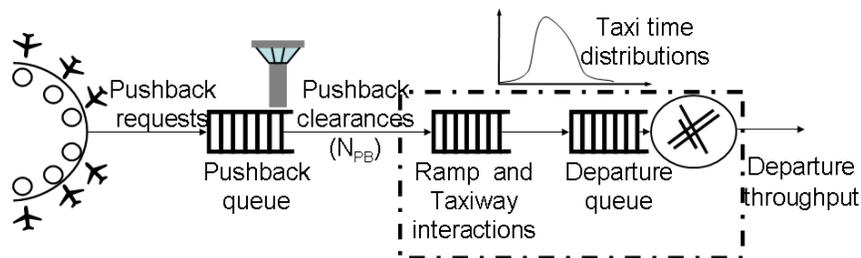
Figure 19: Integrated model of the *controlled* departure process

A. Potential benefits of queue management strategies

The models of departure operations developed so far allow us to estimate the potential benefits of the proposed queue management strategy. In the following discussion, we present the results for the configurations "22L, 27 | 22L, 22R", "4L, 4R | 4L, 4R, 9" and "7, 32 | 33L", which account for 62.5% of VMC flight conditions in BOS. These configurations correspond to 54% of VMC departures in 2007. We also present the tradeoffs involved in selecting N_{ctrl} at values different from the N^* in Table 3.

Table 13 shows the results of the model in terms of taxi-out times, delays and annual taxi-out time reductions for the segment (22L, 27 | 22L, 22R; VMC) if the queue management strategy were to be implemented over all occurrences of this segment in a year that lasted four hours or longer. We present the expected taxi times for a range of values of N_{ctrl}, namely: 10, 15, 16, 17, 18, 19, 20, 21 and 22. The surface saturation point was estimated to be $N^* = 16$ (Table 3), but we also evaluate the strategies of controlling surface traffic to smaller and larger values of N^* to compare expected benefits and costs. The taxi time savings are calculated by comparing the expected taxi-out times with and without control (Tables 5 and 13). In Table 13, the mean delay/flight is defined as the sum of mean taxi time and the mean gate holding time subtracting the expected taxi time of the base case (without control).

In Table 13, we also list more detailed information for the flights that would be held in the *virtual departure queue* for different values of N_{ctrl}:

- The total number of gate-held flights: the total number of flights that would be held in the *virtual departure queue*

- The mean gate-holding time: The mean time spent in the *virtual departure queue* (computed over all flights that are held in the *virtual departure queue*)

- The mean delay of held flights: the sum of mean taxi time and the mean gate holding time minus the mean taxi time of the base case (without control) (computed over all flights held in the *virtual departure queue*)

- The mean taxi-out time of held flights (without control): The mean taxi time of flights which get held in the *virtual departure queue*, in the base case (without control)

- Total duration of the policy: Total time for which the policy would be activated (measured as the sum of all instances that a flight is held in the *virtual departure queue*)

Table 13: Taxi-out time reduction for different values of N_{ctrl} in segment (22L, 27 | 22L, 22R; VMC)

Ncontrol	10	15	16	17	18	19	20	21	22
Mean taxi time (min)	17.70	19.12	19.33	19.51	19.68	19.82	19.94	20.03	20.10
Mean delay/flight (min)	23.38	0.72	0.34	0.15	0.06	0.02	0.01	0.00	0.00
Total number of gate-held flights	33374	11109	8406	6440	4933	3747	2828	2103	1536
Mean gate-holding time (min)	30.75	6.91	6.33	5.93	5.65	5.46	5.31	5.22	5.19
Mean delay/ held flight (min)	27.52	2.24	1.25	0.65	0.32	0.17	0.13	0.12	0.10
Mean taxi time of held flights, no control (min)	21.25	26.08	27.40	28.66	29.89	31.13	32.36	33.61	34.98
Total duration of the policy (hours)	1022	279	207	156	119	90	68	50	37
Annual taxi time reduction (hours)	1729	781	646	523	413	317	237	175	128

We note that the taxi time savings increase by decreasing the value of N_{ctrl}. These savings are however at the cost of increasing the total departure delay. We also observe that choosing N_{ctrl} at the value estimated to be marginally higher than the surface saturation point (16, in this case) decreases the expected taxi times without increasing the expected departure delays. If we choose a smaller value of N_{ctrl}, we operate the airport at a smaller throughput than the maximum achievable, and the expected departure delay increases. A significant portion of the increased delay is incurred at the gate, and the total taxi-out times and emissions decrease. We also include the extreme case of $N_{ctrl} = 10$. The results show that while the taxi-out times decrease significantly, the average delay increases to 23.38 min per flight as a consequence of a considerable under-utilization of resources. The calculations are repeated for the next two most frequently used configurations (Tables 14 and 15).

Table 14: Reduction in taxi-out time for different values of N_{ctrl} in segment (4L, 4R | 4L, 4R, 9; VMC)

Ncontrol	10	15	16	17	18	19	20	21	22
Mean taxi time (min)	16.88	17.99	18.11	18.21	18.29	18.36	18.41	18.46	18.49
Mean delay/flight (min)	16.27	0.74	0.41	0.22	0.12	0.06	0.03	0.01	0.01
Total number of gate-held flights	20635	5858	4312	3168	2289	1633	1169	832	592
Mean gate-holding time (min)	23.52	6.27	5.70	5.29	5.02	4.89	4.81	4.77	4.78
Mean delay/ held flight (min)	21.10	2.94	2.07	1.45	0.95	0.60	0.38	0.24	0.16
Mean taxi time of held flights, no control (min)	19.73	23.83	24.88	25.95	27.06	28.20	29.33	30.46	31.58
Total duration of the policy (hours)	602	142	102	74	52	37	26	19	13
Annual taxi time reduction (hours)	775	270	218	172	135	103	79	59	43

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Table 15: Reduction in taxi-out time for different values of N_{ctrl} in segment (7, 32 | 33L; VMC)

Ncontrol	10	15	16	17	18	19	20	21	22
Mean taxi time (min)	19.17	20.75	20.90	21.01	21.12	21.20	21.27	21.33	21.37
Mean delay/flight (min)	31.89	1.78	1.02	0.57	0.31	0.16	0.09	0.04	0.02
Total number of gate-held flights	17938	6943	5115	3734	2675	1881	1336	958	688
Mean gate-holding time (min)	37.76	7.53	6.55	5.88	5.44	5.19	5.05	4.91	4.79
Mean delay/ held flight (min)	34.97	4.79	3.50	2.52	1.75	1.15	0.77	0.47	0.28
Mean taxi time of held flights, no control (min)	22.17	25.26	26.30	27.37	28.51	29.69	30.92	32.17	33.40
Total Duration of the policy (hours)	574	180	130	93	65	45	32	22	16
Annual taxi time reduction (hours)	798	260	210	170	135	106	82	64	48

Given the new taxi-out times (under N-control) for flights in BOS, we can estimate the fuel burn and emissions by assuming that each flight taxis at 7% throttle setting, and using the fuel burn and emissions indices from ICAO.[8, 16] We can similarly also compute the baseline fuel burn and emissions, and the reduction when $N(t)$ is controlled to be less than or equal to the saturation value (Table 16).

Table 16: Estimated fuel burn and emissions reduction from controlling $N(t)$ to within N^**

Reduction in:	Fuel burn (gallons)	HC (kg)	CO (kg)	NOx (kg)
22L, 27 — 22L, 22R	146,445	988	10,385	1,856
4L, 4R — 4L, 4R, 9	35,583	244	2,595	450
27, 32 — 33L	17,150	123	1,270	216

B.   Operational challenges

Queue management strategies require a greater level of coordination among traffic on the surface that is currently employed. For example, if gate-hold strategies are to be used to limit surface congestion, there need to be mechanisms that can manage pushback and departure queues depending on the congestion levels. In addition, ATC procedures need to also be addressed: for example, currently, departure queues are First-Come-First-Serve (FCFS), creating incentives for aircraft to pushback as early as possible. If gate-hold strategies are to be applied, virtual queues of pushback priority will have to be maintained. We note that the Department of Transportation's airline on-time performance metrics are calculated by comparing the scheduled and actual pushback times; this again creates incentives for pilots to pushback as soon as they are ready rather than to hold at the gate to absorb delay. In addition, gate assignments also create constraints on gate-hold strategies; for example, an aircraft may have to pushback from its gate if there is an arriving aircraft that is assigned to the same gate. This phenomenon is a result of the manner in which gate use, lease and ownership agreements are conducted in the US; in most European airports, gate assignments appear to be centralized and do not impose the same kind of constraints on gate-hold strategies.

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IX.   A predictive model of departure operations

Two key advantages of the proposed model are that (1) it offers a novel method that estimates, at any time, both the number of aircraft in the taxiway system and in the runway queue, and (2) it allows us to estimate, for each flight, the time of arrival at the departure queue as well as the wheels-off time.

The data available from ASPM does not allow us to validate all these estimates, since we only know the pushback and wheels-off times of each flight. However, we believe that the validation that we have presented using these available quantities suggests that the other estimates, namely, the states of the runway queue and the time of arrival at the runway queue are accurate as well. In the future, we would like to validate our estimates of these quantities using a combination of operational observations and surface surveillance data.

A.   Estimating the states of surface queues and taxi-out times

Given the times at which flights call for pushbacks clearance, we would like to estimate the amount of time it will take them to taxi to the runway, the amount of time that they will spend in the runway queue, the overall state of the airport surface (for example, the number of departures on the ground), and the length of the departure queue. In order to achieve the above, we consider two approaches to predicting the desired variables, using Equation 9:

- Model 1 generates $\tau_{unimped}$ for each flight using a normal random variable with mean and standard deviation (corresponding to the particular airline) as given by Equations 7 and 8.

- Model 2 assumes the $\tau_{unimped}$ of each airline to be the mean of the random variable, given by Equation 7.

Figure 20 shows the results of making predictions using the pushback schedule from a 10-hour period on July 22, 2007, along with observed data. The estimates are obtained through 100-trial Monte Carlo simulations, and the average and standard deviation of these trials are presented. The first subplot shows the observed and predicted number of departures in a 15-minute interval, the second subplot contains the average taxi-out times of the flights that depart in the corresponding 15-minute interval, and the third subplot shows the average predicted departure queue size for each 15-minute interval.

We note that the model predictions match the observations reasonably well. We also compute the root mean square error (RMSE), the root mean square percentage error (RMSPE), the mean error (ME), and the mean percentage error (MPE) between the observed measurements and the average of the results of the 100 trials.

Table 17: Evaluation of model predictions using Monte Carlo simulations.

	RMS Error	RMS % Error	Mean Error	Mean % Error
Model 1 (# of departures)	1.477	0.200	1.171	0.142
Model 2 (# of departures)	1.423	0.186	1.103	0.133
Model 1 (Taxi-out time)	2.222	0.157	1.725	0.119
Model 2 (Taxi-out time)	2.111	0.151	1.627	0.112

Figure 20 shows that both models have comparable performance. The difference between the two models is in the way the unimpeded taxi time is generated, and we would expect that as the number of trials increases, the average of the unimpeded taxi times generated in Model 1 tends to the deterministic value (average unimpeded taxi time) assumed by Model 2. Table 17 shows that the errors are also comparable. However, we note that because Model 2 uses a deterministic unimpeded taxi-out time, estimates from Model 2 will have a smaller variance than those from Model 1.

X.   Extensions and next steps

A promising next step will be to examine additional factors that may influence the departure rate of an airport and the taxi-out times. In particular, the role of other parameters such as the arriving traffic
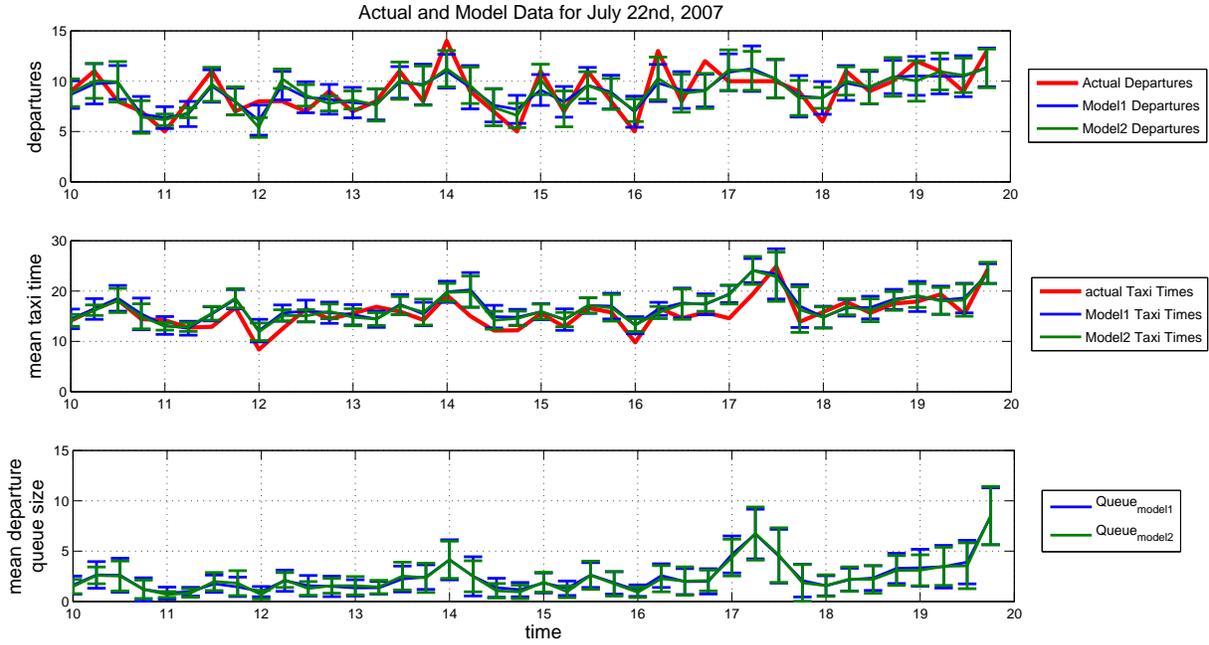
Figure 20: Prediction of departure throughput, average taxi-out times and departure queue lengths in each 15-min interval over a 10-hour period on July 22, 2007. The error bars denote the standard deviations of the estimates.

will need to be studied and possible seasonal variations or daily patterns in the observed data will have to be identified. The use of analytic dynamic models for the runways service process instead of the current simulation-based ones will also be pursued.

Another extension that we are currently researching involves the development of predictive congestion control algorithms. As seen in the last section, the model proposed in this paper can be used to yield predictions of departure processes. A very promising manner to implement queue management therefore is to dynamically modify the pushback schedule so as to minimize the departure queue without increasing the total departure delay. We are also currently continuing to translate the taxi-time reduction benefits into reduction in emissions. This is essential so as to assess the environmental impact of the proposed strategies and to compare them with other proposed operational concepts, such as operational tow-outs and single-engine taxiing.

Finally, we are also applying the techniques proposed in this paper to the modeling of operations at additional airports (such as DTW and EWR), so as to better quantify the impact of surface congestion on emissions and be able to do cross-airport comparisons between different strategies to reduce emissions.

XI. Conclusion

We presented a new queuing network model of the departure processes at airports that can be used to develop queue management strategies to decrease fuel burn and emissions. A predictive model that is capable of estimating taxi-out times and the state of surface queues was also presented. This model has the potential to provide some of the information that is required to improve coordination of departure processes, and thereby increase surface efficiency. A new approach to estimating unimpeded taxi-out times was also proposed and the model was validated using data from 2008. A preliminary estimate of fuel burn and emissions reduction from queue management was also determined. The next steps include a more thorough investigation of the trade-offs between the taxi-out times and total departure delays, a thorough validation of the predictive model, extensions to other airports, and a comprehensive assessment of the emissions impacts of the proposed queue management strategies.

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XII. Acknowledgments

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