



**OPPORTUNITIES FOR REDUCING SURFACE EMISSIONS THROUGH SURFACE
MOVEMENT OPTIMIZATION**

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Report No. ICAT-2008-07
December 2008

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Opportunities for Reducing Surface Emissions through Airport Surface Movement Optimization*

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December 16, 2008

Technical Report #: ICAT-2008-7

Abstract

Aircraft taxiing on the surface contribute significantly to the fuel burn and emissions at airports. This report is an overview of PARTNER's Project 21, which tries to identify promising opportunities for surface optimization to reduce surface emissions at airports, estimate the potential benefits of these strategies, and assess the critical implementation barriers that need to be overcome prior to the adoption of these approaches at airports. We also present a new queuing network model of the departure processes at airports that can be used to develop advanced queue management strategies to decrease fuel burn and emissions.

*This work was supported by FAA, NASA and Transport Canada under the Partnership for Air Transportation Noise and Emissions Reduction(PARTNER)

1 Introduction

Aircraft taxiing on the surface 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 proportional to 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 [10]; 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].

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 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.

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

Table 2: Top 10 airports with the largest taxi-out times in the United States in 2007 [22].

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.

The *taxi-out time* is defined as the time between the actual pushback and takeoff. This is the 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. Surface emissions from departures are therefore 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). For this

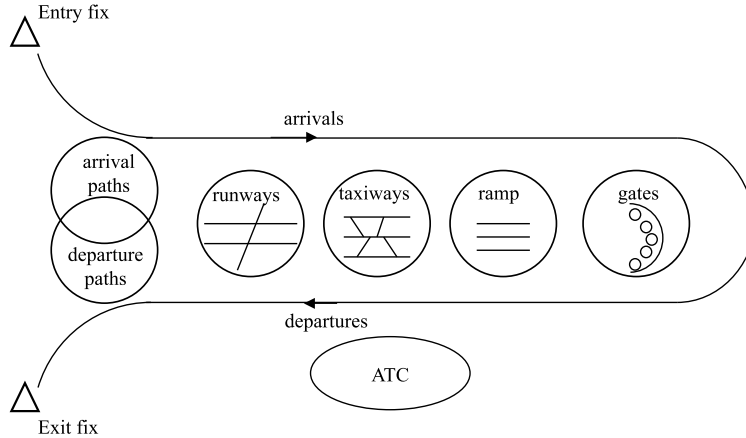


Figure 1: A schematic of the airport system, including the terminal-area [18].

reason, 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 [12].

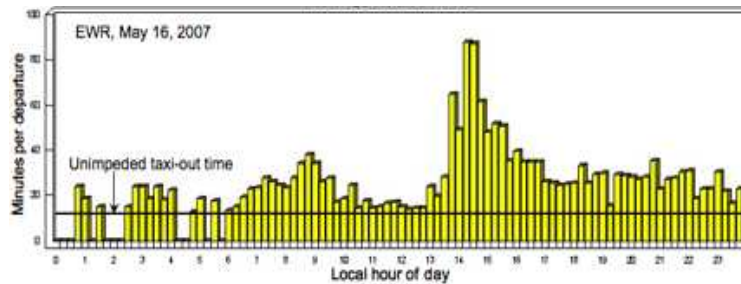


Figure 2: The average departure taxi times at EWR over 15-minute intervals and the unimpeded taxi-out time (according to the ASPM database) from May 16, 2007. We note that large taxi times persisted for a significant portion of the day [10].

In the current work, we consider three possible approaches to reduce emissions at airports: the first is to reduce taxi times by limiting the build-up of queues on the airport surface, the second is to use fewer engines to taxi (and thereby reduce the fuel burn and emissions), and the third is to tow aircraft out close to the runway prior to starting their engines. We estimate the potential benefits of each of these approaches and also assess the operational barriers that need to be addressed before they can be adopted.

2 Baseline emissions

The baseline aircraft emissions for 2007 were computed using a combination of flight data, airline fleet data and aircraft engine emissions and fuel burn data.

2.1 Data sources

The flight schedule data was obtained from the Bureau of Transportation Statistics [22]. This data is the same as the ASQP data [9], and corresponds to “all domestic non-stop flight segments flown

by U.S. carriers with at least 1 percent of passenger revenues in the previous year”. The BTS records include aircraft tail numbers, scheduled arrival and departure times, origin and destination airports, the On, Off, Out and In (OOOI) times, and thereby the taxi-in and taxi-out durations. The aircraft tail numbers in the BTS database are matched with the data in the JP Airline-Fleets International directory [4], to determine the aircraft model, number of engines and engine models used for a particular flight segment. In addition, the engine make and model can be matched to their fuel burn and emissions indices (for different pollutants) using the ICAO Engine Emission Databank [19]. BTS estimates that there were 10.38 million scheduled domestic passenger revenue departures in the US in 2007. Of these, there are 7.46 million records in the BTS/ASQP data. 1.57% of these records lack tail number information, and 0.62% of them lack taxi-out time information. Ultimately, 5.57 million flights have all the necessary information (taxi-out times, tail numbers, engine information and emissions indices for HC, CO and NOx), and 5.76 million flights have all the above information except the HC emissions indices. Therefore, in our assessments, we include about 77% of all BTS records and 55% of the estimated 10.38 million flights in 2007.

The amount of missing data also differs (quite significantly) from airport to airport. For example, Table 3 shows the number of departures for which all the associated data (not including the emissions indices for HC) is available, the number of departures for which all the associated data (including HC) is available, the number of BTS departure records and the number of departures estimated by the Airspace System Performance Metrics (ASPM [10]) database for the top 20 originating airports (as measured by the number of ASPM departures). In general, we note that the HC emissions indices alone are missing for many flights, especially at DFW and ORD. A comparison of the two counts is also shown in Figure 3. We note that the ASPM departure counts are available for 77 airports (known as the “ASPM 77”), while the BTS database contains data from 304 origin airports.

Airport	No. of departures		Fuel/CO/NOx data available		HC data available	
	ASPM	BTS	Number	% of ASPM	Number	% of ASPM
ATL	490735	413851	358737	73.1	355517	72.4
ORD	454568	375784	313001	68.9	288407	63.4
DFW	336397	297345	183836	54.6	120058	35.7
LAX	315456	237597	159719	50.6	155718	49.4
DEN	305534	240928	210819	69.0	203035	66.5
IAH	290527	200420	185925	64.0	184304	63.4
CLT	241322	127108	100565	41.7	99551	41.3
PHX	239472	211072	192035	80.2	190137	79.4
PHL	232042	104063	76478	33.0	74566	32.1
DTW	228255	177478	117656	51.5	116308	51.0
LAS	223126	183668	160323	71.9	159011	71.3
MSP	214251	155846	115589	54.0	113129	52.8
JFK	209500	126366	98043	46.8	97846	46.7
EWR	208583	154113	137614	66.0	135341	64.9
LGA	190948	122899	89597	46.9	81614	42.7
BOS	182759	128320	96561	52.8	94011	51.4
SFO	174249	138491	100386	57.6	97910	56.2
IAD	171294	91048	80113	46.8	79018	46.1
SLC	171128	147808	119799	70.0	118206	69.1
MCO	170533	129778	107712	63.2	105295	61.7

Table 3: Total number of departures in ASPM and BTS databases for different airports. and the flights for which taxi-time, engine and emissions data are all available.

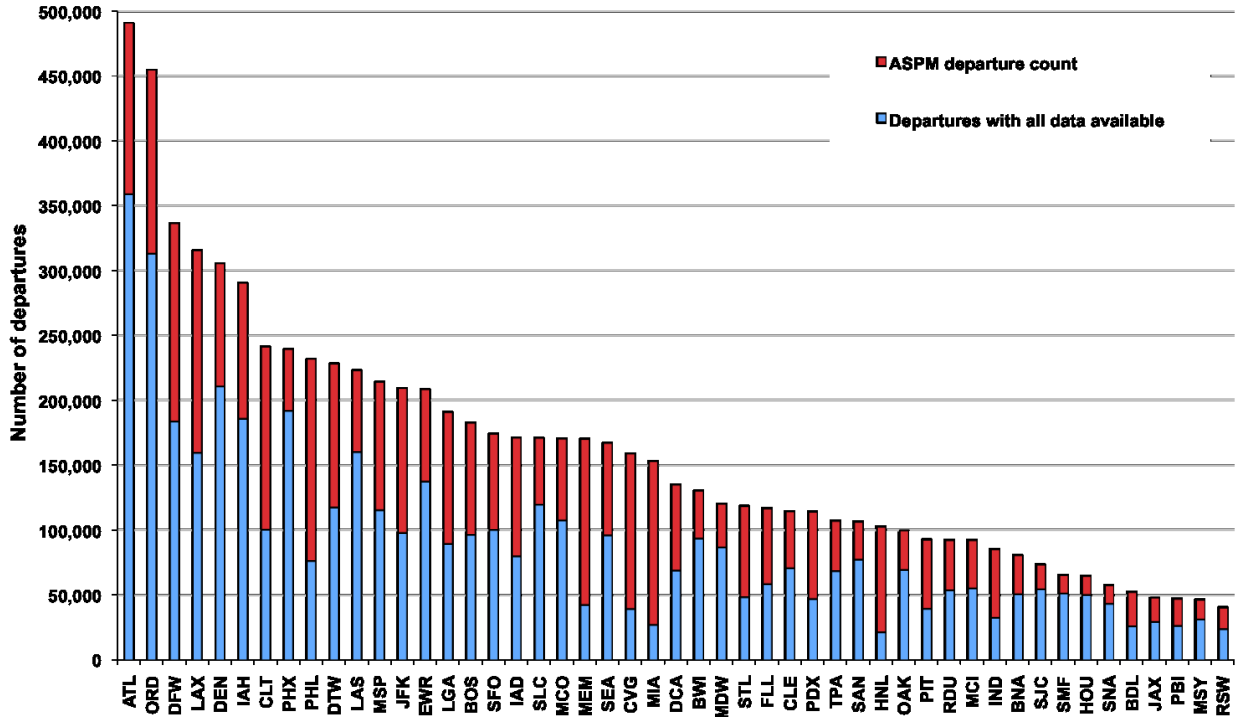


Figure 3: Comparison of departures for which all data is available, and total ASPM departure count for 2007.

2.2 Methodology for estimation of baseline emissions

For each flight record in the 2007 BTS database, we estimate the emissions contribution of the taxi-out portion of the flight. We focus on three pollutant species, namely, CO, NO_x and HC. For each flight, we use the tail number to determine the type and number of engines used, and then the fuel burn and emissions indices from the ICAO engine databank.

Using the above information, the taxi-out fuel burn of flight i in kg, denoted FB_i , is given by

$$FB_i = T_i \times N_i \times FBI_i, \quad (1)$$

where T_i is the taxi-out time of flight i , N_i is the number of engines on flight i and FBI_i is the fuel burn index of each of its engines (in kg/sec).

The emissions from flight i for each pollutant species j (denoted E_{ij} , in kg) is given by

$$E_{ij} = T_i \times N_i \times FBI_i \times EI_{ij}, \quad (2)$$

where EI_{ij} is the emissions index for pollutant j from each engine on flight i , measured in grams of pollutant per kilogram of fuel consumed. We can sum the above quantities over all departures in the system or in any particular airport in order to obtain the total fuel burn and emissions.

In reality, the taxi-out emissions from an aircraft depend on factors for which data is not available, such as the throttle setting, ambient temperature, number of engines used to taxi, etc. We assume that in the baseline case, all engines are used to taxi-out, and that the throttle setting is 7% of maximum thrust. Recent experiments have shown that these assumptions may be quite strong, and that the actual emissions are nonlinear in the low-throttle setting regimes for some

pollutants [14, 15, 16]. We are currently working on leveraging these experimental studies to refine our emissions estimates. We also note that some flights do already either adopt single engine taxiing, or stop their engines when a large delay is expected (even away from the gate). In addition, some flights return to their gates when a large delay is assigned to them. These events are not reported in the BTS data, and hence we ignore their effects in calculating the baseline fuel burn and emissions.

2.3 Baseline emissions estimates

We present two sets of estimates: the first is an estimate of emissions obtained through the aggregation of estimates from Equations (1-2) for all flights for which data are available; the second is an estimate obtained by scaling the results from the previous step proportionately to the total number of flights in the ASPM records. In Figure 4 and the discussion below, “raw” or “unscaled” refers to the contribution of flights for which all the data is available, while “scaled” implies that these values have been scaled to the ASPM departure count for airport k using the formula

$$FB_k^{\text{scaled}} = \frac{FB_k^{\text{unscaled}} \times (\text{ASPM departure count of } k)}{\text{Number of departures from } k \text{ with data available}}. \quad (3)$$

Table 2.3 shows the scaled and unscaled fuel burn and emissions for the top 20 airports (as measured by the ASPM departure count) along with the unscaled and ASPM departure counts.

	Raw emissions (kg)/fuel (gal)				Scaled emissions (kg)/fuel (gal)				Departure count	
	HC	CO	NOx	Fuel	HC	CO	NOx	Fuel	Unscaled	ASPM
ATL	193375	2039187	363479	29129468	264528	2789510	497222	39847714	358737	490735
ORD	129900	1745597	274507	21971419	188652	2535112	398664	31908856	313001	454568
DFW	47134	829335	150830	12232769	86249	1517580	276000	22384445	183836	336397
LAX	74677	804811	140372	10981814	147492	1589557	277244	21689837	159719	315456
DEN	106555	1103306	166677	13549440	154427	1598990	241560	19636819	210819	305534
IAH	90296	1064689	172448	13338263	141097	1663686	269468	20842412	185925	290527
CLT	56282	575474	92146	7240239	135058	1380943	221119	17374126	100565	241322
PHX	56266	807600	165489	12353982	70165	1007096	206369	15405696	192035	239472
PHL	65161	634558	110130	8590475	197705	1925313	334146	26064371	76478	232042
DTW	120886	742905	132092	11714156	234521	1441251	256261	22725698	117656	228255
LAS	62595	817680	165936	12466008	87115	1137988	230938	17349292	160323	223126
MSP	86185	667450	129372	10904776	159749	1237158	239799	20212643	115589	214251
JFK	93699	1067920	214886	16490657	200218	2281950	459172	35237525	98043	209500
EWR	91208	1133733	195992	15174146	138245	1718411	297067	22999614	137614	208583
LGA	72348	694759	130470	10615395	154187	1480662	278056	22623396	89597	190948
BOS	54779	581653	106174	8402538	103679	1100883	200953	15903309	96561	182759
SFO	50997	587693	106448	8290787	88520	1020112	184771	14391064	100386	174249
IAD	35077	448250	77099	5997524	75000	958428	164850	12823635	80113	171294
SLC	53653	644433	97057	7597778	76641	920546	138642	10853117	119799	171128
MCO	34112	449326	94046	7187196	54007	711387	148897	11378993	107712	170533

Table 4: Scaled and unscaled fuel burn, emissions and departure counts for the top 20 airports (as measured by the ASPM departure count).

We also consider potential metrics to compare the relative fuel burn and emissions performance of different airports. One possible approach is to normalize the fuel burn at an airport by the maximum fuel burn among all airports (i.e., the fuel burn of ATL) and to compare this value with the departure count at the same airport normalized using the departure count of ATL. This would allow us to draw conclusions of the form “Airport i consumes a fraction x of the fuel consumption at ATL, but faces (only) a fraction y of the ATL departure demand”. These metrics are plotted

in Figure 4 (using the unscaled data) and in Figure 5 (using the scaled data). Airports for which the departure metric (denoted by the lines with markers) is less than the fuel burn or emissions metric (denoted by the bars) can be considered to have weak emissions/fuel burn performance. We note that these airports are consistent between the unscaled plots (Figure 4) and the scaled plots (Figure 5).

We also plot, for each of the top 20 airports, the fraction of the total taxi-out emissions or fuel burn (from the top 20 airports) associated with that airport and the fraction of the top 20 airport departure demand that is associated with it. These plots are shown in Figure 6.

3 Single-engine taxiing

Fuel burn and emissions can potentially be reduced if all aircraft were to taxi out using only a subset of their engines. This translates to using one engine for twin-engine aircraft, and is therefore referred to as *single-engine taxiing*. Aircraft engines must be warmed up prior to departure, for a period that ranges from 2-5 min depending on the engine type. Therefore, even if an engines power is not required for taxiing, it is assumed that all engines must be on for a minimum of five minutes before takeoff. Thus, if the taxi time of an aircraft is less than five minutes, a single-engine taxi-out scenario would not change either the activities of the pilot or the surface emissions of that flight. Conversely, if an aircraft taxis for longer than five minutes, the emissions are reduced by the amount of pollutants that one of its engines would produce for the duration of the taxi time in excess of five minutes (for example, if the taxi time is twelve minutes its emissions will be reduced by the amount of one engine operating for seven minutes).

This procedure is not recommended for uphill slopes or slippery surfaces, or when deicing operations are required [2]. Aircraft manufacturers (for example, Airbus) recommend that airlines adopt single-engine taxiing whenever conditions allow it, and yet few airlines have done so. There is a potential for significant savings from single-engine taxiing; for instance, American Airlines is estimated to save \$10-\$12 million a year in this manner [13].

3.1 Potential benefits of single-engine taxiing

We estimate the theoretical benefits of single-engine taxiing at airports in the US. For each of the top 50 airports, and for each departure operation at the airport, we estimate the reduction in fuel burn and different emissions were the aircraft to taxi out with one of its engines off. The engine start-up time is assumed to be 5 min for all aircraft.

Using the above information, the single-engine taxi-out fuel burn of flight i in kg, denoted FB_i^{single} , is given by

$$FB_i^{\text{single}} = ([T_i \times (N_i - 1)] + \min\{T_i, 300\}) \times FBI_i, \quad (4)$$

where T_i is the taxi-out time of flight i in seconds, N_i is the number of engines on flight i and FBI_i is the fuel burn index of each of its engines (in kg/sec).

The single-engine taxi-out emissions from flight i for each pollutant species j (denoted E_{ij} , in kg) is given by

$$E_{ij} = ([T_i \times (N_i - 1)] + \min\{T_i, 300\}) \times FBI_i \times EI_{ij}, \quad (5)$$

where EI_{ij} is the emissions index for pollutant j from each engine on flight i , measured in grams of pollutant per kilogram of fuel consumed. We can sum the above quantities over all departures in the system or in any particular airport in order to obtain the total fuel burn and emissions from single-engine taxiing.

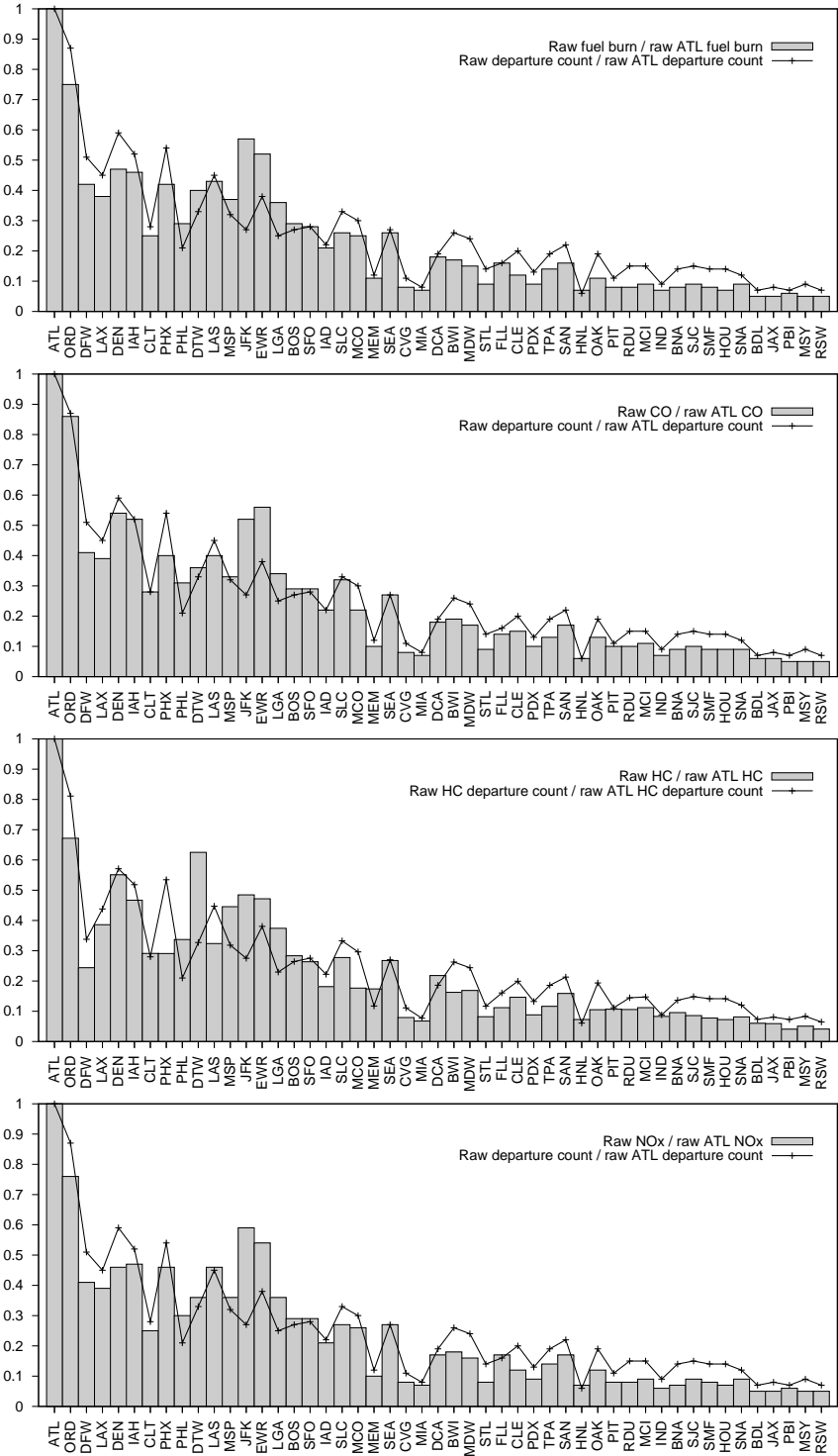


Figure 4: [Bars] Baseline unscaled fuel burn/emissions normalized by the unscaled ATL fuel burn/emissions; [Line] Raw departure count at airport divided by raw departure count at ATL.

The percentage reductions in fuel burn, HC and CO emissions with respect to the baseline scenario are shown in Figure 7. For example, at both JFK and PHL, more than a 40% decrease in taxi-out fuel burn can theoretically be achieved if all aircraft were to taxi with one engine off (as

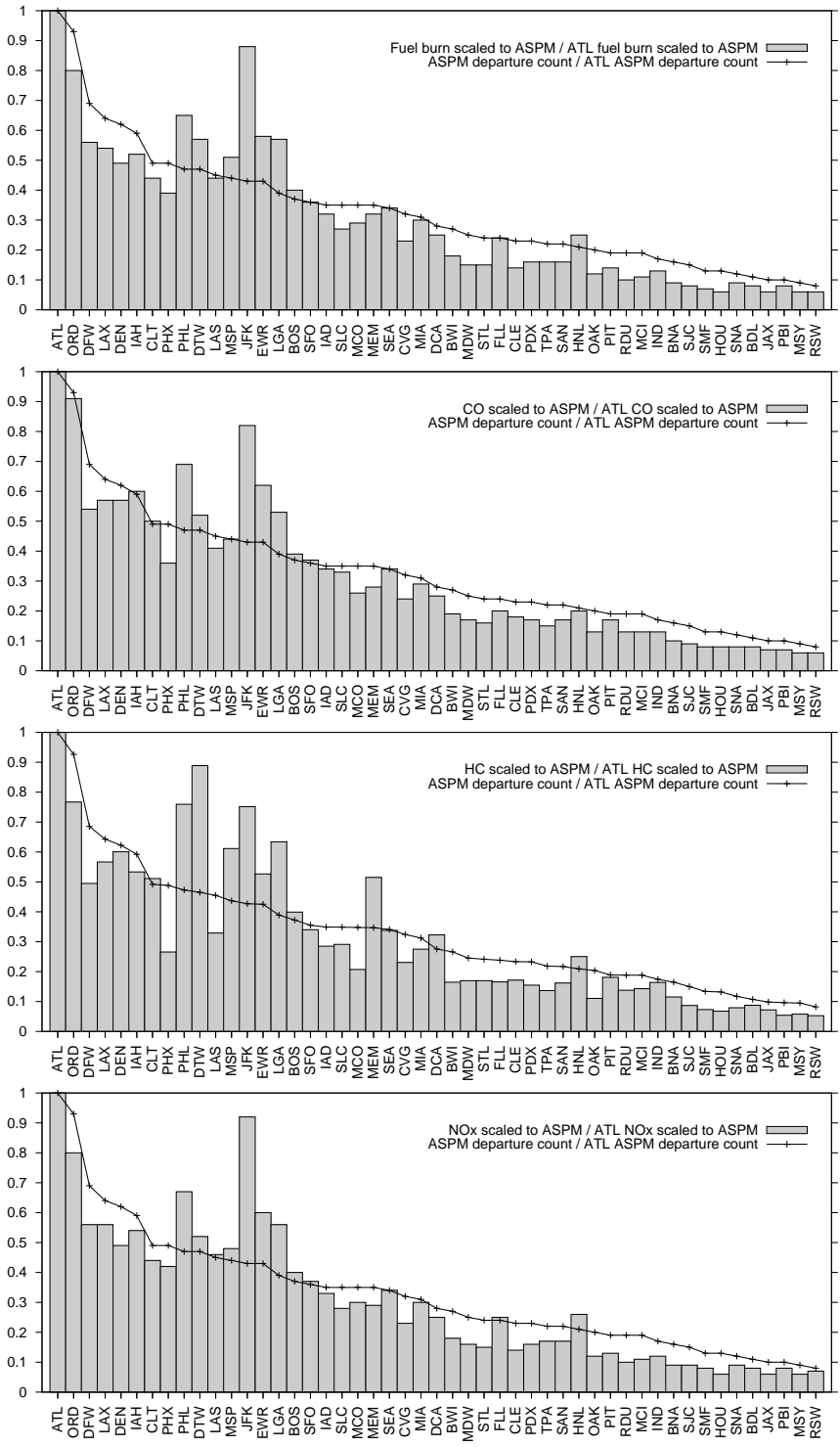


Figure 5: [Bars] Baseline scaled fuel burn/emissions normalized by the scaled ATL fuel burn/emissions; [Lines] ASPM departure count at airport divided by ASPM departure count at ATL.

opposed to taxiing on all engines), with a 5 min start-up time.

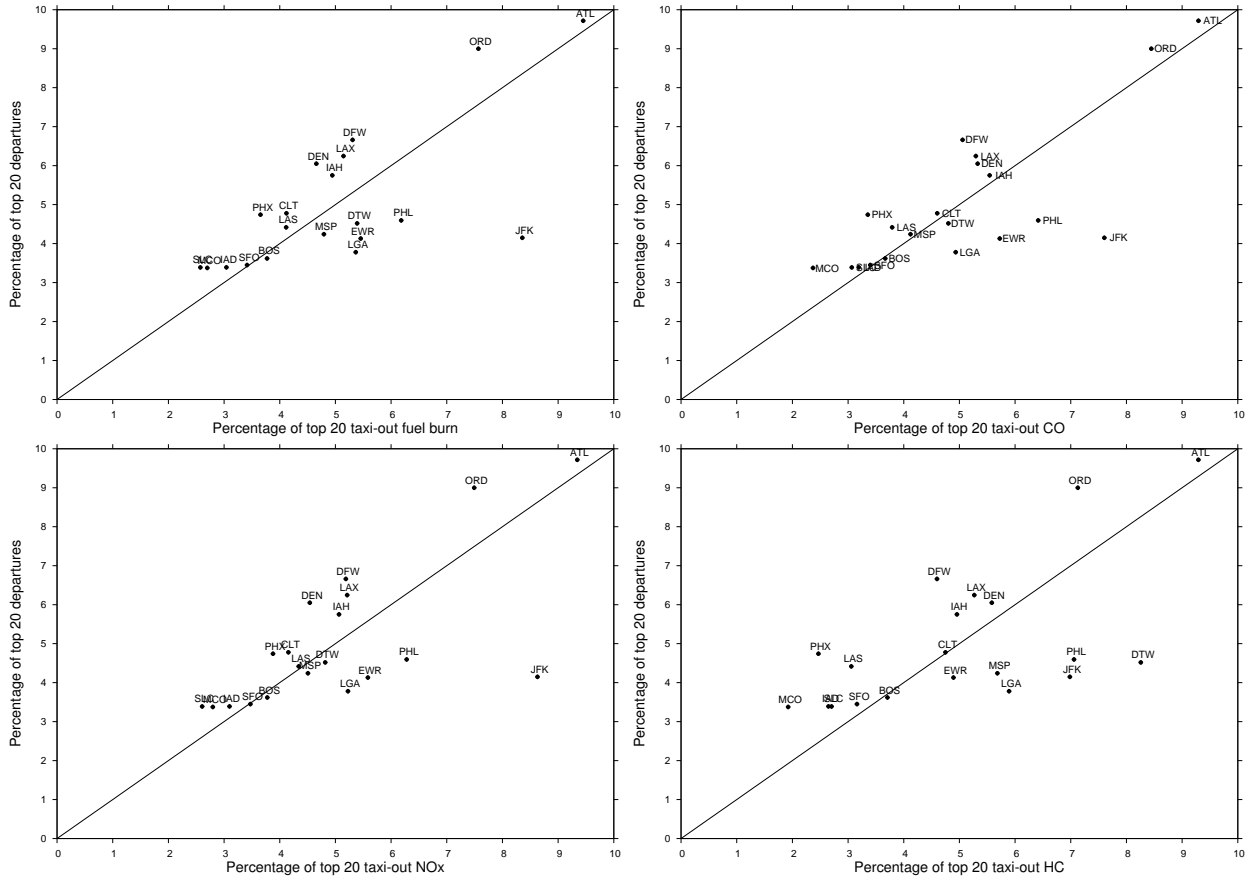


Figure 6: Percentage of top 20 departure demand that each airport accounts for vs. the associated fuel burn (top, left) and emissions as a fraction of total taxi-out fuel burn/emissions from the top 20 airports. The solid line denotes the 45° line. Points that fall below this line are considered to be weak performers: we note that JFK tends to be a significant outlier in all the plots.

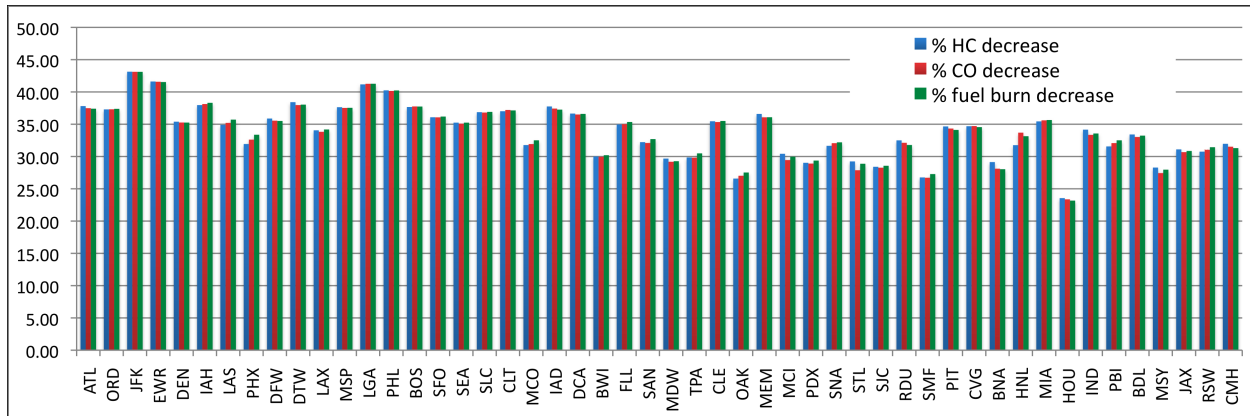


Figure 7: Potential reductions in fuel burn and emissions from single-engine taxiing (compared to baseline emissions) at the top 50 airports in the United States.

3.2 Operational challenges

Successful implementation requires improved dissemination of information (for example, knowledge that an aircraft is 5 min from take-off requires information on the status of the departure queue,

downstream airspace conditions, and congestion levels on the surface), as well as strategies to increase robustness to unexpected events (such as the detection of mechanical problems during engine start, which would now be closer to the runway, requiring routing of the aircraft back to the gate, as well as assigning it a later departure time). In Section 8, we present a predictive model of the departure process that allows us to estimate the taxi-out time for a flight, the state of the departure queue, etc. In addition, during current operations, fire protection from ground staff is not available during engine start if it takes place outside the ramp area. The frequency and impact of such events will have to be evaluated in order to assess the feasibility of single-engine taxiing. It has also been noted that taxiing out on a subset of engines results in reduced redundancy, and increases the risk of loss of braking capability and nose wheel steering [2]. Some difficulties on tight taxiway turns during single-engine taxiing have been reported by pilots. This appears to be particularly true when there is asymmetry, as in the case of a twin-engine aircraft; it can be difficult to turn in the direction of the engine that is being used. While taxiing on fewer engines, more thrust per engine is required to maneuver, especially on breakaways and 180 degree turns. As a result, care must be taken to avoid excessive jet blast and foreign object damage. For high bypass ratio engines, the warm-up time prior to maximum takeoff thrust and the cool-down time after reverse operation have a significant effect on engine life. However, it appears that 5 min is generally sufficient time for the warm-up process.

4 Operational tow-outs

Another approach that has been proposed to reduce surface fuel burn and emissions is that of towing aircraft to the runway, rather than using the engines to taxi. This procedure is alternatively known as *dispatch towing*. During departure tow-outs, the engines are not turned on until five minutes before takeoff (that is, for warm-up). The power required to tow the aircraft to the runway is generated by tugs. As result, aircraft emissions decrease, but tug emissions are introduced.

4.1 Potential impact

Emissions from tugs depend on the fuel that powers the tug as well as the required engine horsepower. We consider three different tug fuel types: diesel, gasoline, and compressed natural gas (CNG). We assume that two different brake horsepower (BHP) settings are required for each engine type; one to tow narrow-body aircraft and one to tow wide-body aircraft. The brake horse power values for each aircraft and tug engine type, and the corresponding fuel consumption, NOx, and CO emission coefficients are shown in Table 5. The CO₂ emission factors are assumed to be 22.23 lb CO₂/gallon of fuel for diesel tugs and 19.37 lb CO₂/gallon of fuel for gasoline tugs, as opposed to 20.89 lb CO₂/gallon of jet fuel burned [8].

Aircraft type	Tug fuel type	BHP	Fuel consumption (gal/BHP-hour)	Emissions (g/(BHP-hr))		
				NOx	CO	HC
Narrow body	Diesel	175	0.061	11.0	4.0	1.0
Narrow body	Gasoline	175	0.089	4.0	240.0	4.0
Narrow body	CNG	175	- n/a -	6.0	120.0	2.0
Wide body	Diesel	500	0.053	11.0	4.0	1.0
Wide body	Gasoline	500	0.089	4.0	240.0	4.0
Wide body	CNG	500	- n/a -	6.0	120.0	2.0

Table 5: Tug Brake Horse Power (BHP) specifications and characteristics for different aircraft types.

As in the case of single engine taxiing, we assume that the engine start-up time is 5 min. We also assume that the tugs travel significantly slower than aircraft taxiing on their own engines; we model this by assuming that the taxi time of an aircraft being towed is 2.5 times its value otherwise.

Using the above information, the single-engine taxi-out fuel burn of flight i in kg, denoted FBI_i^{tug} , is the sum of the fuel consumption in the tug and the fuel burn of the aircraft. The tow-out emissions of pollutant j for flight i using a tug type k are denoted E_{ijk}^{tug} , and are given by

$$E_{ijk}^{\text{tug}} = (T_i \times 2.5 \times \text{BHP}_{ki} \times EI_{kj}^{\text{tug}}) + (300 \times N_i \times FBI_i \times EI_{ij}), \quad (6)$$

where T_i is the taxi-out time of flight i in minutes (and is greater than 5 min), N_i is the number of engines on flight i , FBI_i is the fuel burn index of each of its engines (in kg/sec), BHP_{ki} is the brake horse power of tug type k to tow flight i , EI_{ij} is the emissions index for pollutant j from each engine on flight i , measured in grams of pollutant per kilogram of fuel consumed, and EI_{kj}^{tug} is the emissions index for pollutant j from a tug of type k , measured in grams of pollutant per BHP-sec. We note that these calculations do not include the contribution of the tugs on their return trips to the ramp areas.

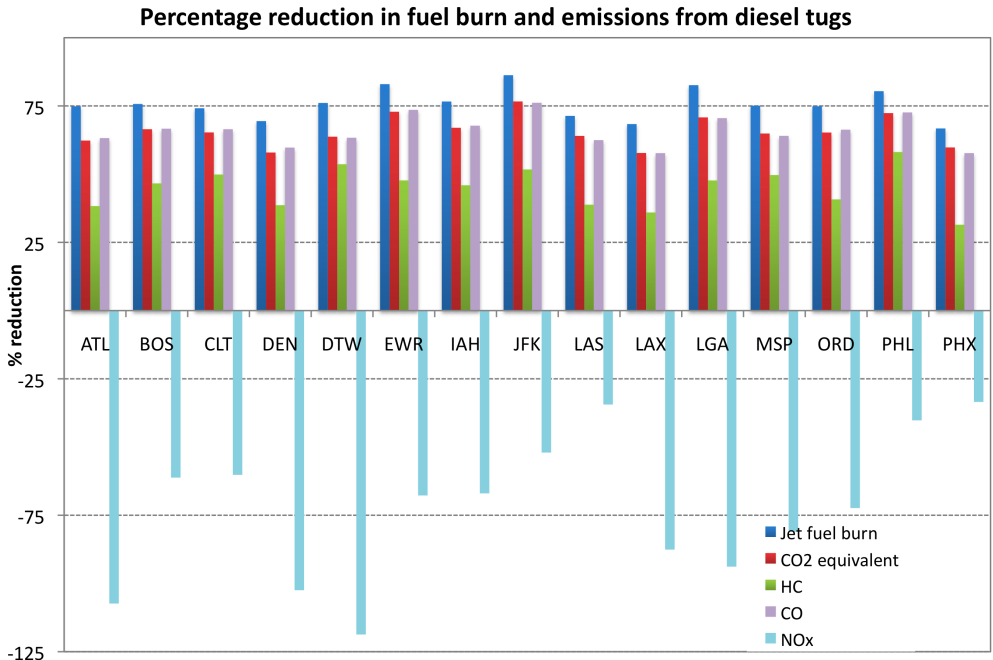


Figure 8: Potential reductions in fuel burn and emissions from operational tow-outs using diesel tugs at the top 15 airports in the United States. Negative values imply an increase in emissions.

4.2 Operational challenges

Although it was pursued in the past by Virgin Atlantic for their 747 fleet, tow-outs had to be abandoned after Boeing suggested that the nose landing gear on the 747s were not designed to withstand such loads on a regular basis [1]. This concept is currently being revisited by Airbus, which is considering other means of dispatch towing which will not impose the same loads on the nose gear. Our studies have found that before tow-outs are adopted, other factors such as the emissions characteristics of the tugs (for example, diesel tugs will potentially increase NOx

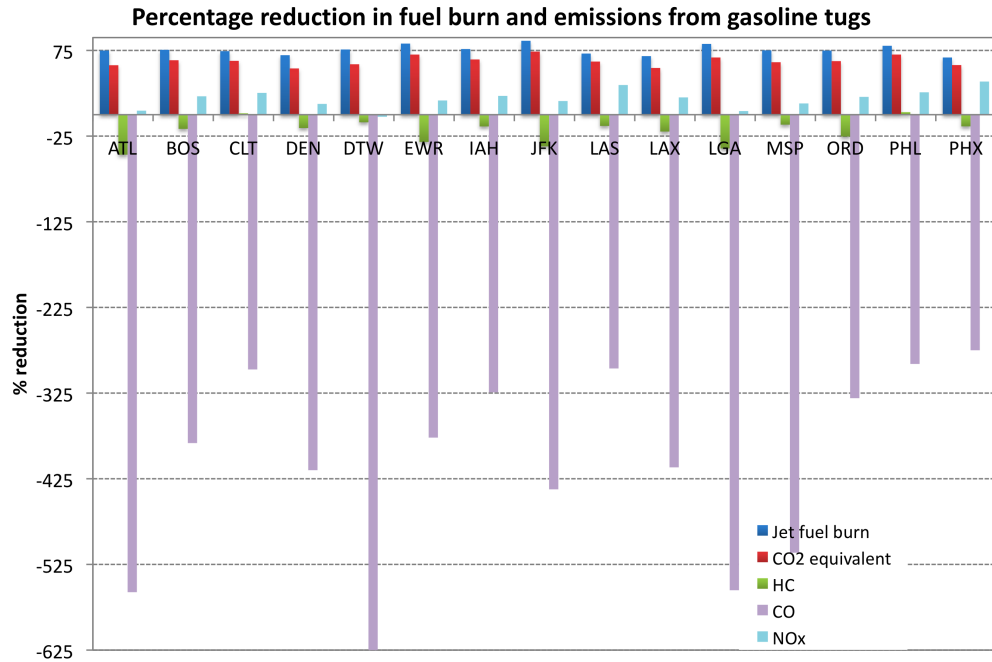


Figure 9: Potential reductions in fuel burn and emissions from operational tow-outs using gasoline tugs at the top 15 airports in the United States. Negative values imply an increase in emissions.

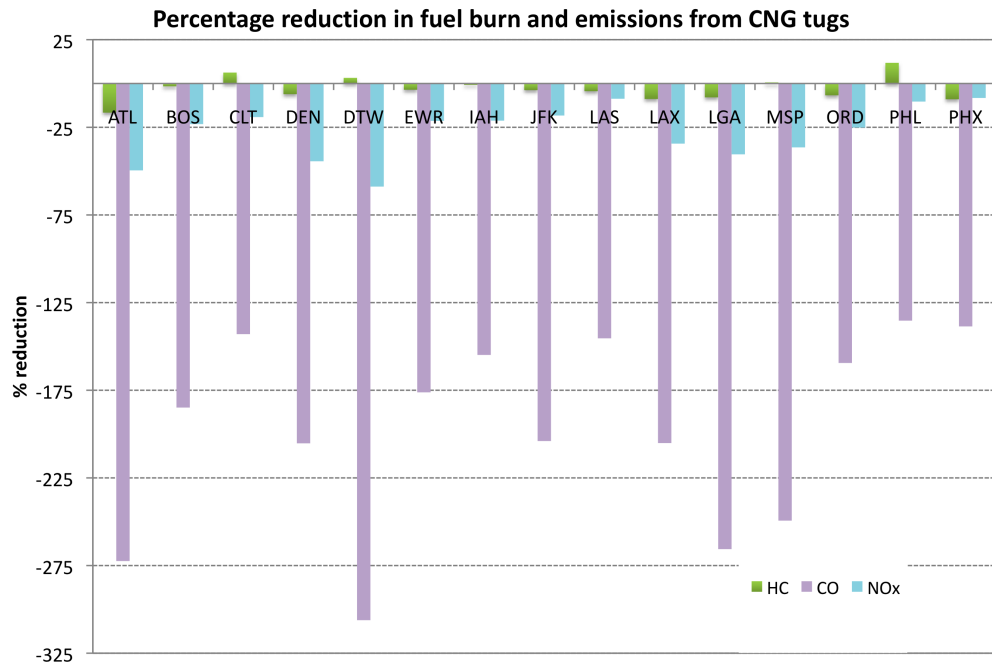


Figure 10: Potential reductions in emissions from operational tow-outs using CNG tugs at the top 15 airports in the United States. Negative values imply an increase in emissions.

emissions), the impact of tow-outs on taxi times and airport throughput (because of reduced speeds: for example, Virgin Atlantic at Heathrow found a 3x increase on the A340-500 taxi time when

compared to the normal dispatch procedure), and information requirements (as in the case of single-engine taxiing, a good estimate of the take-off time improves the benefit of tow-outs) will need to be considered. Other operational issues such as communication protocols between the ATC, the cockpit and the tug operator will also have to be evaluated and addressed. If a viable operational towing concept is developed before the proposed field trials, we will also evaluate it in cooperation with the airframe manufacturers. As in the case of single-engine taxiing, tow-outs will require that (all) the engines be started away from the ramp area, with the associated challenges.

5 Advanced queue management

Another promising mechanism by which to decrease taxi times, and to thereby decrease fuel burn and emissions, is 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, aircraft taxi-out procedures can be managed to achieve considerable reductions in fuel burn and emissions.

5.1 Potential benefits

For example, in PHL, we have estimated that if every departure taxied out for the unimpeded taxi time (depending on its terminal, season, etc. – approximated by the tenth percentile of ASPM taxi-out times for the given terminal and season), we would achieve a theoretical reduction in taxi-out emissions and fuel burn of nearly 60%. Done naively, this would be equivalent to allowing only one (or very few) aircraft to taxi out at any given time. This would result in a decrease in airport throughput, and an increase in departure delays. However, we believe that improved queue management when done right has the potential to decrease taxi-out delays in addition to emissions and fuel burn.

5.2 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 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.

In this work, we focus on modeling the taxi-out process as a queuing network. Our rationale for applying this modeling approach is the fact that the queues which are formed in the system during the taxiing process offer a suitable control point, and proper modeling of the queues enables the application of strategies to control them. Ideally, one would like maintain the surface queues

as close as possible to the smallest loads which will keep the airport throughput at its capacity limit. This approach will decrease taxi-out times without sacrificing the airport's throughput. In the remainder of this report, we describe such a model of airport taxi-out operations that we have developed.

6 A queuing model of the departure process

Our primary objective is to construct a model for each airport which describes the departure process. 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

6.1 Model inputs

The inputs to the model are based on the explanatory variables identified in previous studies [17]. Idris *et al.* [17] identified the runway configuration, weather conditions and downstream restrictions, the gate location, and the length of the take off 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, and 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 [21]. Furthermore, we use the general weather conditions (VFR vs. IFR) and the runway configuration as surrogates for weather and downstream airspace conditions. To summarize, the inputs to the model are

- The pushback schedule, PS
- The gate location of the departing flight, GL
- The runway configuration, RC
- The reported flight rules (IFR or VFR), FR

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 take-off. $Q(t)$ 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 take-offs during period t .
- $N_Q(i)$ = the number of departing aircraft on the surface when aircraft i pushes back that will take off before aircraft i (the length of the takeoff queue [17]).
- $\tau(i)$ = the taxi time of each departing aircraft. This is the third output of the model.

Using the above notation, the following relations are satisfied:

$$N(t) = Q(t) + R(t) \tag{7}$$

$$N(t) = \min(C(t), Q(t)) \tag{8}$$

$$N(t) = N(t-1) + P(t-1) - T(t-1) \tag{9}$$

Combining Equations (7) and (9), we get

$$Q(t) = Q(t-1) - T(t-1) + R(t-1) - R(t) + P(t-1), \tag{10}$$

which is the update equation of the departure queue.

6.2 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 conceptualized 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 or to enter a taxiway segment in which another aircraft is taxiing. We cumulatively denote these spatially distributed queues 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 take-off. We model the departure process as a server, with the departure runways “serving” the departing aircraft. This conceptual model of the departure process is depicted in Figure 11.

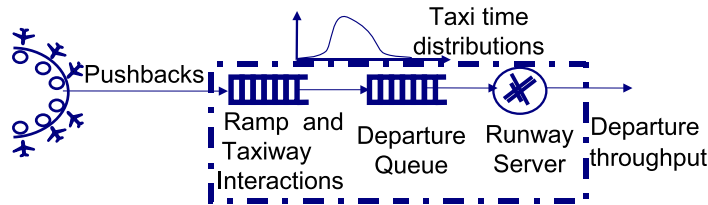


Figure 11: Integrated model of the departure process

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

$$\tau = \tau_{unimpeded} + \tau_{tw} + \tau_{queue} \quad (11)$$

The first term of Equation (11), $\tau_{unimpeded}$, 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, τ_{tw} , reflects the delay due to aircraft interactions on the ramp and the taxiways. In other words, τ_{tw} 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. The third term, τ_{queue} , is the time the aircraft spends in the departure queue. Naturally, 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 (9) and (10) as aircraft take-off and push back. Therefore, assuming that Equation 11 is an appropriate way to describe the departure process, the model may be built using the following steps:

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

Then, given a pushback schedule and gate locations, we can use Equations (9- 11) to get the outputs of the models.

In order to extract the aforementioned dependencies, we study a dataset of observations from aircraft taxiing out at an airport. Combining the observations with the explanatory variables, we can mathematically describe $\tau_{unimpeded}$, τ_{tw} and τ_{queue} and construct the requisite model.

6.3 Data requirements

Ideally, we would like a dataset which consists of $\tau_{unimpeded}$, τ_{tw} and τ_{queue} , in order to study how these variables change with the model inputs. However, this information is not available. The only information we have for flights departing from an airport of study during a time period consists of

1. Actual pushback time times
2. Actual take-off times

In addition to these, we possess the following information about the explanatory variables

1. Pushback schedules
2. Runway configuration
3. Reported flight rules, and
4. Gate location for each departing flight

6.3.1 Data Sources

As seen in Section 2.1, the BTS database offers a wealth of data which enables the study of the on-time performance of the US 21 top carriers [22]. For every recorded flight, the BTS database contains the fields (1-2) identified above. However, the airports we consider also serve a significant number of flights that are not present in this dataset. These include flights of regional and international carriers, cargo, general aviation and air taxi operations, and military flights. Such flights account for 20-35% of the total traffic at some of the airports that we examine (Table 3). The ASQP database [9] contains departure information aggregated by the number of departures per 15-minute interval at each airport. While this data resolution is smaller than needed in (1-2), it complements the BTS data in terms of offering the departure throughput of the airport, the demand profile over a 15-minute interval and the total number of departures during a time period of interest (for example, an hour, a day, a month or a year).

Items 2 and 3 were obtained from the ASPM database [10], where runway configurations and weather conditions are reported in 15-minute intervals. Gate and terminal information can be obtained from the airline information in some cases; for example, at BOS, the airline operating a flight is a sufficient proxy for the gate and terminal information because there is no dominant airline and each major airline uses a spatially proximate and small (less than 10) set of gates. However, in the case of DTW, NWA uses more than 100 gates which may be separated by as much as 1.6 km. In such a scenario, the airline assignment alone does not offer enough information on the starting point of a departing flight. In this case, terminal and gate information from flightstats.com may be used to supplement the data [6]. In addition, this information can be used to study the interactions between arriving and departing traffic, gate use constraints, etc.

6.4 Model development for BOS

In this section, we analyze how we can get estimates of the three terms of Equation (11), given a set of the explanatory variables (RC, RD, TG, 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 $\tau_{unimpeded}$, τ_{tw} and τ_{queue} , but instead only the actual pushback and take-off times of flights. As a result, the calibration of the model makes several assumptions which are analyzed in the next few sections.

6.4.1 Unimpeded taxi-out times

According to the FAA, the unimpeded taxi-out time is defined 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*. 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 1 AND the arrival queue is equal to 0*. Then, a linear regression of the observed taxi times with the observed departure and arrival queues is conducted, and the unimpeded taxi time is estimated from this equation by setting the departure queue equal to 1 and arrival queue equal to 0 [11].

In the present work, we use the observations of [17] that there is poor correlation of the taxi-out times with arriving traffic, and that the taxi-out time of a flight $\tau(i)$ is more strongly correlated to its take-off queue than the number of departing aircraft on the ground ($N(t)$).

In figure 12 we show the scatter of $\tau(i)$ vs. $N_Q(i)$ in BOS for runway configuration 4L, 4R / 4L, 4R, 9 under VFR, as well as the linear regression fit and the smoothing-spline fit.

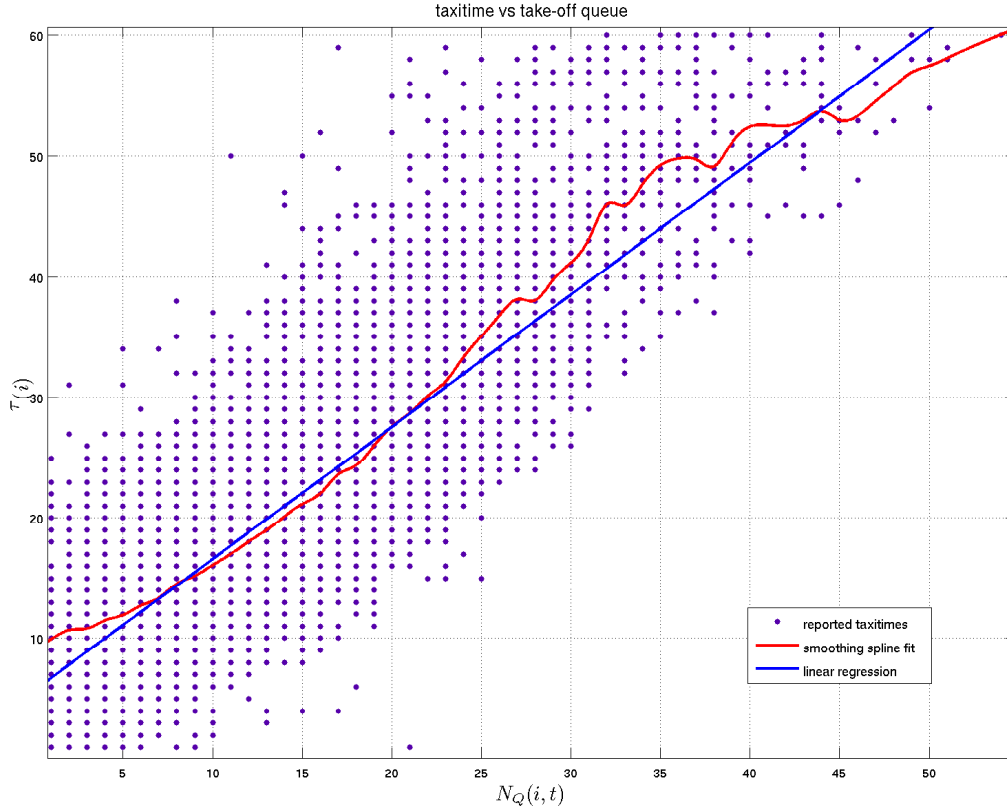


Figure 12: $\tau(i)$ vs. $N_Q(i)$ scatter

The smoothing spline fit indicates that the linear regression is barely appropriate for getting a good estimation for the unimpeded taxi-out time, since the taxi time does not depend linearly on the take-off queue. While the linear regression gives a good fit for much of the data, it is not a good approximation for the regime that we are interested in, namely for low values of the take-off queue length. We note that in Figure 12, the linear regression fit deviates significantly from the smoothing spline fit for $N_Q(i) \leq 8$. The ASPM database corrects for this effect by excluding the highest 25 percent of the values of actual taxi 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” [11].

This is an empirical metric, and does not explain why the 75th is an appropriate percentile of the flights to use (or to exclude congestion effects) or why the bias that the flights under medium-traffic conditions introduce is not important. Figure 12 suggests that a piecewise linear regression might be more appropriate. Then, the first line-segment could be used to estimate the unimpeded taxi time. However, there is no rationale for the choice of the number of the segments in the piecewise regression.

We know that by definition, unimpeded taxi times are observed when neither congestion nor other 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 $N_Q(i)$.

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

$$\tau(i) = p_o + p_1 N_Q(i) + W(i), \quad (12)$$

where W_1, \dots, 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 start the linear regression $\tau(i)$ vs. $N_Q(i)$, by keeping $N_Q(i) \leq 3$. We use the t-test to evaluate whether the estimates of p_1 we get have statistical significance. If not, we increment the limit of $N_Q(i)$ (under which flights are included in the regression analysis) by 1 until we obtain a non-negative estimate of p_1 , and the corresponding p_0 . The unimpeded taxi time is therefore calculated as

$$\tau_{unimpeded} = p_o + p_1, \quad (13)$$

and its variance is given by [3]

$$\hat{S}_n^2 = \frac{1}{(n-2)} \sum (\tau(i) - p_o + p_1 N_Q(i))^2. \quad (14)$$

For each pair (RC,FR) in BOS, this regression analysis is conducted for each “gate group”, with the operating airline of a flight serving as a surrogate for the “gate group”. So, for each airline operating in BOS, we calculate the expected unimpeded taxi-out time.

6.4.2 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 moving average of take-off rate over the time periods $(t+dt-n, t+dt-n+1, \dots, t+dt, \dots, t+dt+n)$. The maximum correlation between $N(t)$ and $\bar{T}_n(t)$ is obtained for $n=9$ and $dt=9$ for BOS, for the high throughput configurations used under VFR conditions. This means that the number of departures on the surface at time t ($N(t)$), is a good predictor of the number of take-offs during the time interval $(t, t+1, t+2, \dots, t+18)$ ¹. Under IFR conditions, we obtain the optimal values $(n, dt) = (10, 10)$ for BOS.

As $N(t)$ increases, the take-off rate initially increases, but saturates at a critical value N^* . This is consistent with the findings of prior studies [21, 20]. 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 VFR conditions (Table 6.4.2).

Figure 13 shows the moving average of the take-off rate as a function of $N(t)$. The saturation points are also denoted. We note that the take-off rate initially increases as $N(t)$ increases, but

¹In a prior study, Pujet estimated that $(n, dt) = (5, 6)$ [20]. This discrepancy can be explained by the observation that his data included only 65% of the flights and because traffic in BOS has risen significantly over the past 10 years.

Configuration	N*
27, 32 / 33L	21
22L, 27 / 22L, 22R	19
4L, 4R / 4L, 4R, 9	19

Table 6: Runway saturation points for most frequent configurations used in BOS

subsequently stabilizes at about 0.76 aircraft/min or 46 aircraft/hour. This number can be viewed as the practical departure capacity of BOS for the runway configuration 4L, 4R / 4L, 4R, 9 under good weather conditions.

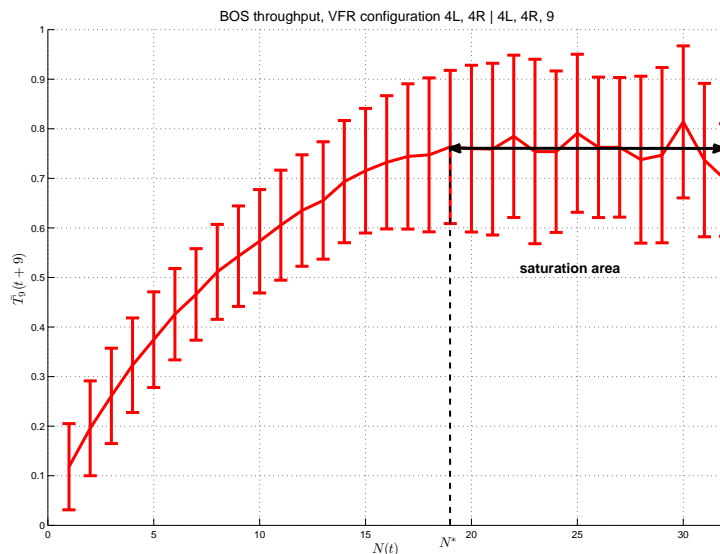


Figure 13: Moving average of take-off rate as function of $N(t)$

6.4.3 Modeling the runway 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 take-off 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 process. By examining the inter-departure times of aircraft in configuration 4L, 4R / 4L, 4R, 9 at BOS when it is experiencing high loads ($N(t) > 19$), it is possible to obtain a histogram of inter-departure times, as shown in Figure 14 (left).

A 1-minute time resolution is available in the data set. We assume that departures which are recorded as taking off during the same minute are separated by 30 sec (whereas in reality this could

be any time between less than a minute). From this histogram, the mean-interarrival departure time is derived as 1.3 min. We observe that 93% of departures are separated by three minutes or less. The distribution (during congested operations) is the result of a combination of endogenous factors such as the departure process (ATC wake vortex separation), and exogenous factors such as communication delays or interactions with arriving traffic. Since the exogenous factors cannot be controlled, the distribution in Figure 14 (left) is simplified by assuming that the inter-departure times take values of either 1, 2 or 3 min. This is also consistent with the observation that the typical runway occupancy time for commercial air carriers is approximately a minute. The probabilities are assigned so that the mean inter-departure time is 1.3 min and the 2 min inter-departure time has the same frequency as in the raw data (Figure 14, right). In this way, we account for the probabilistic nature of the runway service process, but develop a model which is more representative of real operations. 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 τ_{queue}).

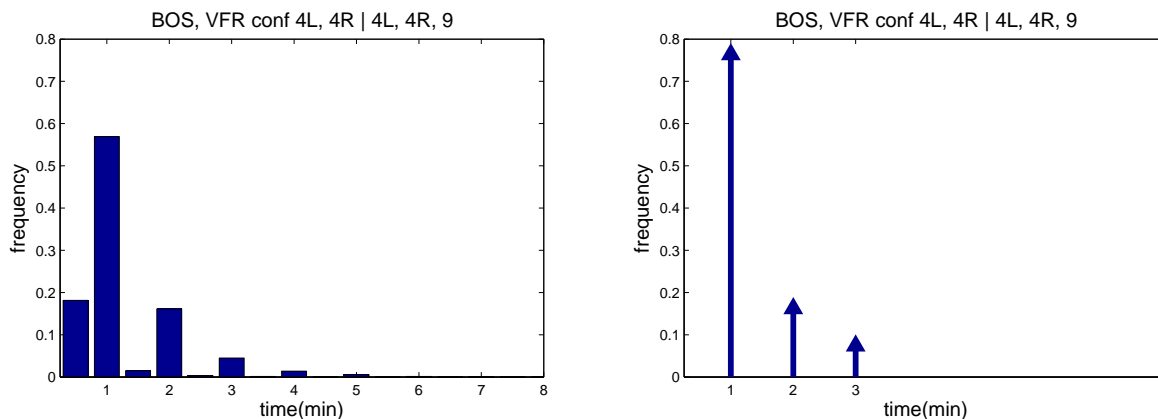


Figure 14: [Left] Histogram of inter-departure times; [Right] Simplified histogram of inter-departure times.

6.4.4 Modeling ramp and taxiway interactions

The remaining unmodeled term in Equation (11), namely τ_{tw} , represents the effect of queuing at the ramp and the taxiways. This term is the most difficult to estimate, since there are no distinct operating conditions at which it is the dominant term. As a first step, we neglect this term. In other words, we assume that aircraft travel 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 VFR conditions. We eliminate certain time periods from the data set to remove bias from exogenous factors:

1. Time periods before 6am and after 9pm (overnight), because of the larger numbers of cargo flights (for which data is not available) and because the less reliable recording of runway configurations, and
 2. The first 30 minutes after a configuration change, to remove artifacts of the transition process.
- Figure 15 compares the performance of the model with the observed data.

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

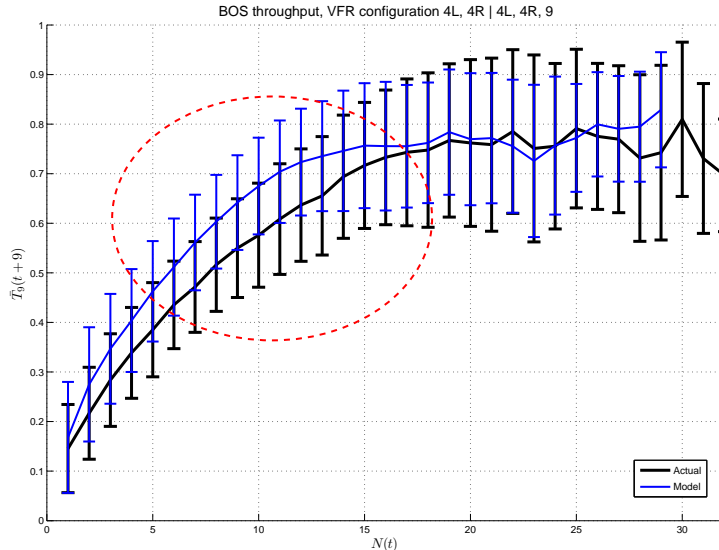


Figure 15: Actual and modeled variation of the take-off rate as a function of $N(t)$, when taxiway interactions are neglected.

runway queue in 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 take-off 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 nominal taxi time leads to predictions that are more optimistic than in real operations, as seen in Figure 15. This is because the model predicts that aircraft reach the runways at a higher rate than reality (since they only taxi for their unimpeded times), and do not wait at the runway (since the runway queues are not saturated). The predicted take-off rates therefore tend to be greater than the observed rates. 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.

We now relax the assumption that the aircraft take just their unimpeded taxi-out time to reach the runway. Equation (11) 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

$$\tau = \tau_{travel} + \alpha R(t) + \tau_{queue} \quad (15)$$

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 is determined through trial-and-error to keep the following metrics as small as possible:

- Mean square error between the actual and the modeled graph of $\bar{T}_n(t + dt)$ vs. $N(t)$.
- Kullback-Leibler (KL) divergence between the distributions of observed and modeled $N(t)$.

We evaluate both metrics because we would like the model to give good estimates of the departure throughput at given values of $N(t)$, and to also yield good predictions of the congestion level on the surface.

Configuration	α
27, 32 / 33L	0.6
22L, 27 / 22L, 22R	0.5
4L, 4R / 4L, 4R, 9	0.5

Table 7: α for different BOS runway configurations

For the most frequently used runway configurations in BOS, the estimated values of α are given in Table 7.

We run the model again using 15 for configuration 4L, 4R / 4L, 4R, 9 under VFR conditions.

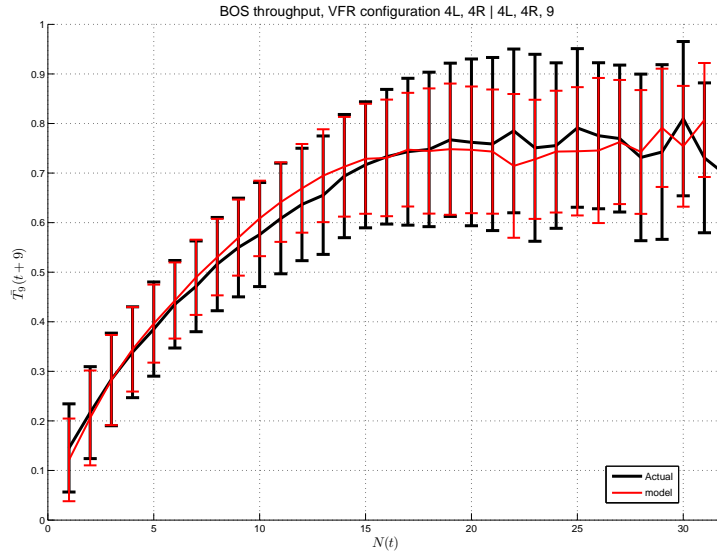


Figure 16: Actual and modeled variation of the take-off rate as a function of $N(t)$, when taxiway interactions are included.

A comparison of Figures 15 and 16 illustrates the benefits of including the taxiway interaction term in the expression for taxi-out time. We also note that the variance of the take-off rate predicted by the refined model is lower than that of the model that neglects the effect of ramp/taxiway congestion.

6.5 Results of modeling

In addition to the plots of throughput as a function of $N(t)$, the typical taxi time distributions predicted and observed over different ranges of $N(t)$ can also be analyzed (shown in Figures 17 and 18 for two frequently used runway configurations).

6.5.1 Predicting runway queues and taxiway congestion

It is possible to use Equation (15) 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 19. We note that as congestion

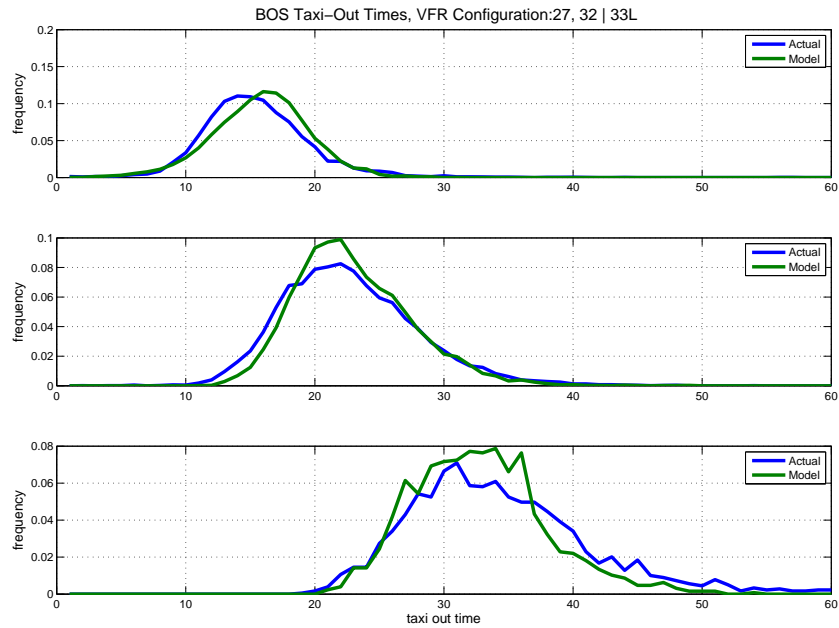


Figure 17: Taxi-out time distributions under low ($N \leq 10$), medium ($10 < N \leq 20$) and heavy ($N > 20$) departure traffic on the surface for configuration 27, 32 | 33L.

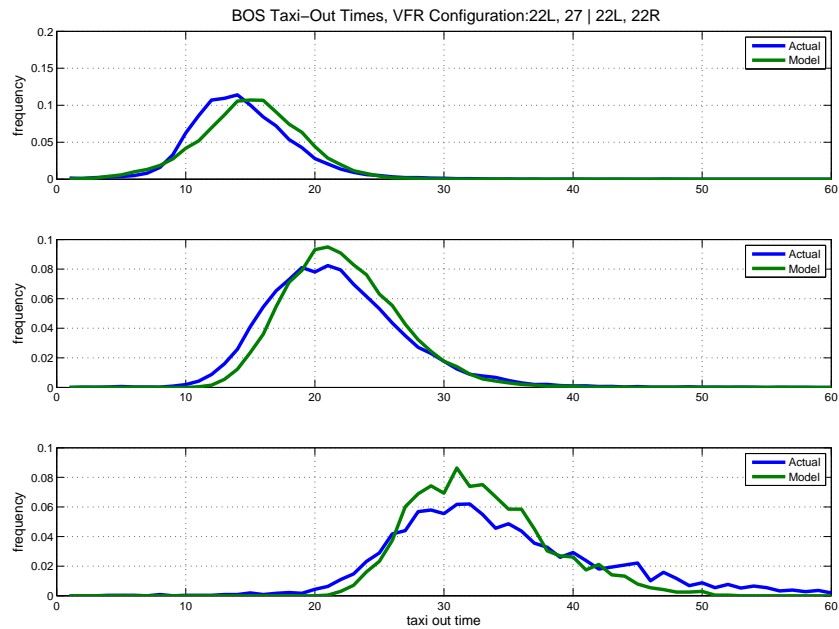


Figure 18: Taxi-out time distributions under low ($N \leq 10$), medium ($10 < N \leq 20$) and heavy ($N > 20$) departure traffic on the surface for configuration 22L, 27 | 22L, 22R.

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.

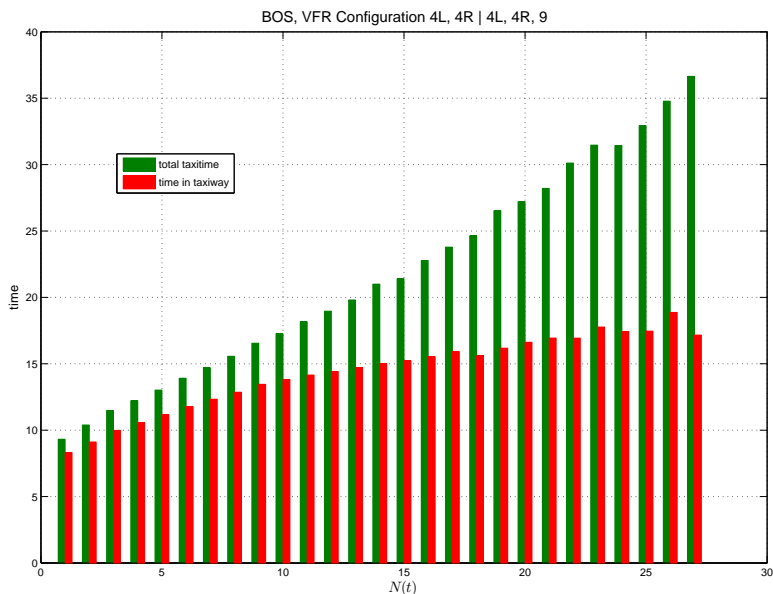


Figure 19: Estimated time spent by an aircraft transiting the taxiways and waiting in the runway queue for different levels of surface traffic.

6.6 Model Validation

The model parameters in the previous sections were identified using BOS operations data from 2007. We validate this model using data from the six months of 2008. We evaluate the performance of the model in terms of throughput 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 6.4 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 first half of the 2008.
2. Comparing the simulation results with the reported departure throughput and taxi-out times for January-June 2008.

Figure 20 shows the comparison between the observed throughput and the throughput of the simulated model. We note that there is a difference between the mean and the standard deviation of the observed throughput and the simulated model at low values of $N(t)$ for the configuration 22L, 27 / 22L, 22R. However, only 22 out of the 11364 aircraft which operated using this runway configuration and in VFR conditions in the steady state departed at $N(t) = 1$. Similarly, only 47 departures were served with only 2 aircraft on the ground ($N(t) = 2$). The low number of operations in this region also explains the large variance of the observed data. Figure 21 shows the taxi time distributions which result from the model.

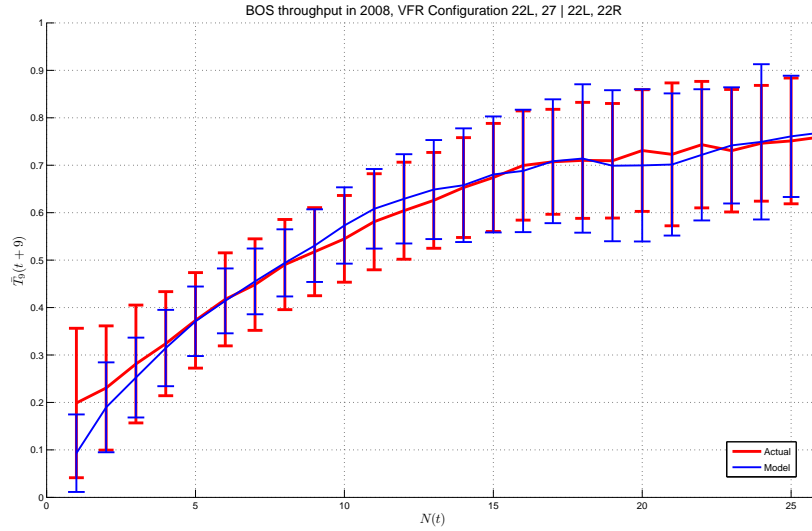


Figure 20: Moving average of take-off rate $\bar{T}_9(t+9)$ as a function of $N(t)$ for configuration 22L, 27 / 22L, 22R in BOS in 2008. The model was derived from a training set of data from 2007.

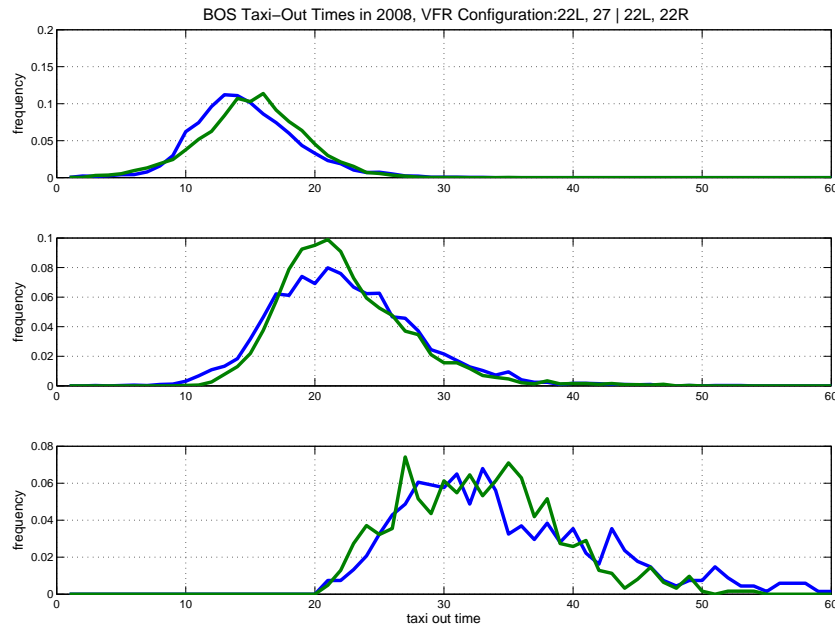


Figure 21: Taxi-out time distributions under low ($N \leq 10$), medium ($10 < N \leq 20$) and heavy ($N > 20$) surface traffic for configuration 22L, 27 / 22L, 22R in BOS in 2008.

7 Management of the pushback queue

The data analysis confirms prior observations [20, 21] 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 is listed in Table 6.4.2. 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.

We would like to use N^* as listed in table 6.4.2 for taxiing operations control. The proposed algorithm, which can be thought of as *virtual departure queuing*, 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*.

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 22.

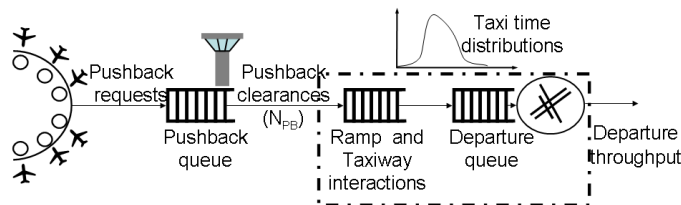


Figure 22: Integrated model of the *controlled* departure process

7.1 Potential benefits of advanced queue management strategies

We have developed suitable models of departure operations that allow us estimate the potential benefits of this 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 were used during 62.5% of VFR flight conditions in BOS. These configurations processed 54% of the VFR departures in 2007.

We also present the tradeoffs involved in selecting N^* at values different from the ones in Table 6.4.2.

First, we compare the actual taxi-out times under configuration 22L, 27 / 22L, 22R (VFR) to the taxi-out times predicted by the model. Since the model is stochastic, the model results are obtained by averaging the predictions from multiple (10) trials. Extremely congested conditions (severe outliers) are omitted, since they may be due to exogenous factors such as mechanical problems or reporting errors. The outliers are defined as values of surface congestion that are experienced for less than 30 minutes a year.

Total flights departing in configuration	32738
Observed mean taxi time (min)	20.05
Expected taxi time from model (min)	19.75

Table 8: Actual and expected taxi times for configuration 22L, 27 / 22L, 22R and VFR.

From Table 8, we see that the results of the model are close to the observed values. Table 9 shows the results of the model in terms of expected taxi-out times, gate holding times and annual taxi-out time reductions if the advanced queue management strategy were to be implemented over all occurrences of this configuration in a year. We present the expected taxi times for four different values of N^* , namely: 19,17,15 and 7. The surface saturation point was estimated to be $N^* = 19$ (Table 6.4.2), but we also evaluate the strategies of controlling surface traffic to smaller 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 8 and 9). In Table 9, the expected departure delay is defined as the sum of expected taxi time and the expected gate holding time. In other words, it is the estimate of the elapsed time between a flight requesting pushback clearance and its take off.

N^*	19	17	15	7
Expected taxi-out time (min)	19.16	18.85	18.42	15.04
Expected gate-holding time (min)	0.57	1.10	2.41	77.70
Total expected departure delay/flight (min)	19.73	19.95	20.83	92.74
Annual reduction in taxi time (hours)	322	491	726	2569

Table 9: Reduction in taxi-out time when $N(t) \leq N^*$, for configuration 22L, 27 / 22L, 22R and VFR.

We note that the taxi time savings increase by decreasing the value of N^* . These savings are however at the cost of increasing the total departure delay. We also observe that choosing N^* at the value estimated to be the surface saturation point (19, in this case) decreases the expected taxi times without increasing the expected departure delays. If we choose a smaller value of N^* , 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 $N^* = 7$. The results show that while the taxi-out times decrease significantly, the average delay increases to 77 min per flight as a consequence of a considerable underutilization of resources.

The calculations are repeated for the next two most frequently used configurations (Tables 10 and 11, and 12 and 13).

Total flights departing in configuration	23111
Observed mean taxi time (min)	18.31
Expected taxi time from model (min)	18.19

Table 10: Actual and expected taxi times for configuration 4L, 4R / 4L, 4R, 9 and VFR.

N^*	19	17	15	7
Expected taxi-out time (min)	17.67	17.4	16.97	13.73
Expected gate-holding time (min)	0.65	1.03	1.87	56.26
Total expected departure delay/flight (min)	18.32	18.43	18.48	69.99
Annual reduction in taxi time (hours)	200	304	470	1718

Table 11: Reduction in taxi-out time when $N(t) \leq N^*$, for configuration 4L, 4R / 4L, 4R, 9 and VFR.

8 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.

8.1 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 15:

- Model 1 generates $\tau_{unimpeded}$ for each flight using a normal random variable with mean and standard deviation (corresponding to the particular airline) as given by Equations 13 and 14.
- Model 2 assumes the $\tau_{unimpeded}$ of each airline to be the mean of the random variable, given by Equation 13.

Figure 23 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

Total flights departing in configuration	16195
Observed mean taxi time (min)	21.06
Expected taxi time from model (min)	20.90

Table 12: Actual and expected taxi times for configuration 7, 32 / 33L and VFR.

N^*	21	19	17	7
Expected taxi-out time (min)	20.63	20.44	20.10	15.47
Expected gate-holding time (min)	0.39	0.83	1.63	65.95
Total expected departure delay/flight (min)	21.02	21.27	21.73	81.42
Annual reduction in taxi time (hours)	73	124	216	1466

Table 13: Reduction in taxi-out time when $N(t) \leq N^*$, for configuration 7, 32 / 33L and VFR.

error (ME), and the mean percentage error (MPE) between the observed measurements and the average of the results of the 100 trials.

	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

Table 14: Evaluation of model predictions using Monte Carlo simulations.

Figure 23 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 14 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 small variance than those from Model 1.

9 Selection of candidate locations for evaluating concepts

There are several factors that could determine the choice of airport(s) for a demonstration of the concepts described in this report. One possible factor is to choose airports where there is the maximum potential for improvement. Figure 6 shows the variations of the percentage of departure operations at an airport (as a fraction of all departures in the top 20 airports) vs. the percentage of fuel burn/emissions during taxi out (as a fraction of the total taxi-out fuel burn/emissions in the top 20 airports). We note the outliers in this plot, namely, airports at which the fuel burn or emissions is disproportionate to the departure demand, and in particular JFK, which has the worst performance by this metric for fuel burn and CO/NOx emissions. We note that the HC emissions alone look different, with DTW having the most disproportionate impact. In addition, ORD and ATL would be interesting studies in best-practices, currently having better fuel burn and emissions performance than other airports.

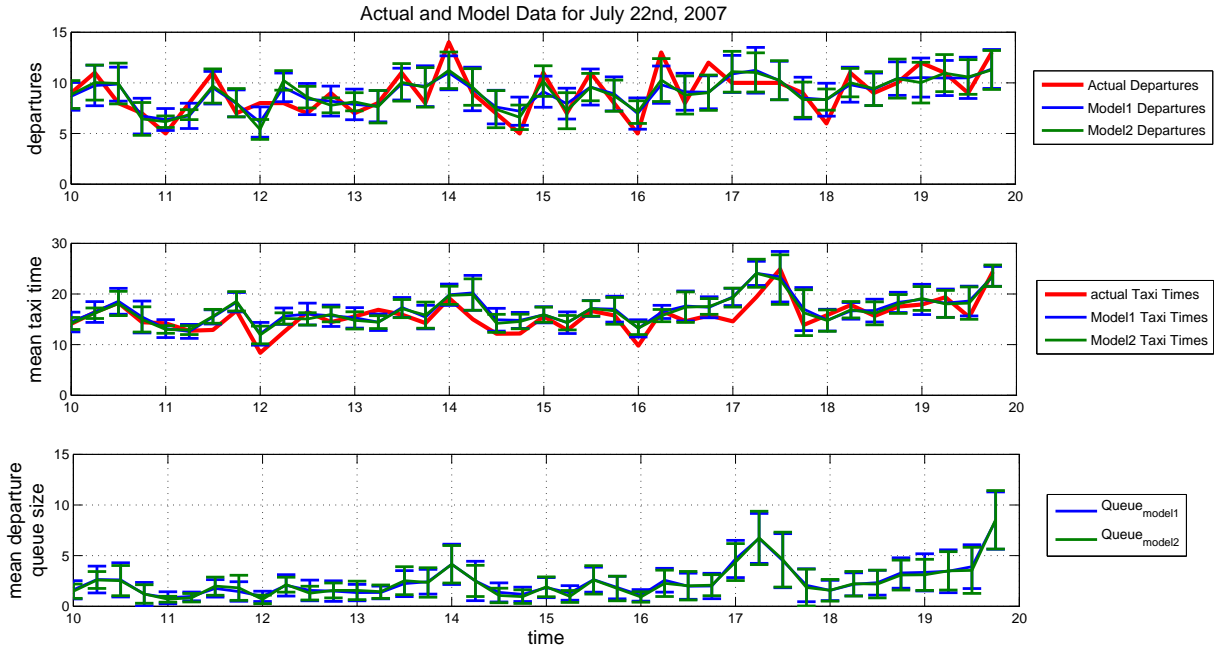


Figure 23: Prediction of departure throughput, average taxi-out times and departure queue lengths in each 15-min interval over a 10-hour period on July 22, 2007. The error bars denote the standard deviations of the estimates.

10 Conclusion

This report presented an overview of PARTNER’s Project 21, which tries to identify promising opportunities for surface optimization to reduce surface emissions at airports. The first part of the report presented estimates of current fuel burn and emissions impacts of airport taxi-out processes, evaluated the potential benefits of proposed strategies to reduce them, and identified some of the critical implementation barriers that need to be overcome prior to the adoption of these approaches at airports. The second part of the report presented a new queuing network model of the departure processes at airports that can be used to develop advanced 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. The next steps include refinement of the emissions inventories using experimental data, integration with local air quality models, a thorough validation of the predictive model, and an assessment of the emissions impacts of the proposed queue management strategies.

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