Impact of Gate Assignment on Departure Metering

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***Abstract*—Departure metering reduces congestion by reducing the number of aircraft present on the airport surface at any time while not starving the runway. Because some departing flights are held at gates, there is a possibility that arriving flights cannot access the gates and have to wait until the gates are cleared. This is called a gate conflict. Robust gate assignment is an assignment that minimizes gate conflicts by assigning gates to aircraft to maximize the time gap between two consecutive flights at the same gate; it makes gate assignment robust, but passengers may walk longer to transfer flights. In order to simulate the airport departure process, a queuing model is introduced. The model is calibrated and validated with actual data from New York's LaGuardia Airport (LGA) and a large U.S. hub airport. Then, the model simulates the airport departure process with the current gate assignment and a robust gate assignment to assess the impact of gate assignment on departure metering. The results show that the robust gate assignment reduces the number of gate conflicts caused by departure metering compared with the current gate assignment. Therefore, robust gate assignment can be combined with departure metering to improve operations at congested airports with limited gate resources.**

***Index Terms*—Airport departure operation, airport gate assignment, departure metering, optimization.**

I. Introduction

DEPARTURE metering is an approach to reduce taxi delays and emissions in the departure process while maintaining airport departure throughput (takeoff rate), which is motivated by the fact that the number of takeoffs per minute is saturated when the number of aircraft that taxis out (denoted as N) is greater than a saturation point N^* [1], [2]. As a result, the takeoff rate corresponding to N^* and above represents the airport's departure capacity. Departure metering manages to keep N near N^* by controlling push-back clearances. Departure metering is equivalent to freeway ramp-metering control in the ground transportation literature [3], [4]. The first analytic assessment of the departure metering was conducted by Pujet *et al.* [5]. When N exceeds N^* or predetermined number N^{ctrl}, departure metering becomes active and aircraft requesting push-back clearance are held at gates. Independent studies [6]–[10] confirm that taxi delays in the departure process indeed can be transformed to gate-holding delays by utilizing departure metering without sacrificing airport capacity. Departure metering was experimentally implemented at Boston's Logan Airport following the development of suitable human interfaces [11], and it was shown that departure metering helps the airport system to shift taxi-out times to environmentally and financially less expensive gate-holding times. The environmental benefits of departure metering are compounded by the possibility for airlines to independently reorganize the priorities of their aircraft within those being held at a given moment, possibly leading to additional economic benefits. This concept, which was proposed and evaluated first in [12], has been field tested at Paris's Charles de Gaulle (CDG) Airport in early 2013 as part of the DFlex program [13]. The results were encouraging enough that DFlex has remained active at CDG since then.

One issue, however, is whether departure metering can be detrimental to the free access of arriving flights to the terminals. This is particularly true for congested and resource-limited airports such as New York's LaGuardia Airport (LGA), New York's John F. Kennedy Airport (JFK), or Hartsfield–Jackson Atlanta International Airport (ATL). Recent studies related to departure metering by Jung *et al.* [7] and Simaiakis *et al.* [11] indicate that the research community is still concerned with the impact of departure metering on terminal airside congestion. At the same time, the rapid move of departure metering techniques toward implementation in Europe, in the United States, and in other congested airport locations means that airlines and airport operators must begin incorporating these new concerns in their operations to reap the benefits of departure metering.

This paper investigates the impact of smart gate assignment on the departure metering described above. Departure metering addresses airport surface congestion by holding an aircraft at its gate, thus taking advantage of the time gap between consecutive uses of the same gate. This gap, which we call gate separation, can constrain the efficiency of departure metering. For instance, when an aircraft is held at the gate and an arriving aircraft requests the same gate, either the gate-held aircraft must be cleared for push-back or the arriving aircraft must wait for the gate hold to terminate, or sometimes, the ramp controller assigns the arriving aircraft to another gate. In both situations, departure metering is prevented from working to its full potential. This paper sheds light on the importance of understanding the impact of gate assignment on departure metering and vice versa.

This paper is organized as follows. Section II presents the airport departure model, a queuing model that consists of a takeoff model and taxi-out time estimates. The model is calibrated and validated with historical data. Section III presents the airport gate assignment problem for robust gate assignments. Section IV analyzes the impact of gate assignment on departure metering, and Section V concludes and summarizes the findings.

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TABLE I
FREQUENTLY USED RUNWAY CONFIGURATION IN LGA

Configuration (Arrival — Departure)	% of Hours	% of Push-backs
31 — 4	17.4 %	22.6 %
4 — 13	15.4 %	19.4 %
22 — 31	14.0 %	18.2 %
13, 22 — 13	12.0 %	14.9 %
22 — 13	7.7 %	10.1 %

II. AIRPORT DEPARTURE MODEL

A. Queuing Model

Many researchers use a queuing model for simulating metered airport departure processes [5], [14]–[16]. The queuing models have a similar structure. When an aircraft is ready for push-back, it enters a push-back queue. When departure metering is inactive, the push-back is cleared on a first-come–first-served (FCFS) basis. However, if departure metering is active, a push-back is cleared only when the number of aircraft on the ramp or taxiway system is below a critical number N^{ctrl} [7], [15], [16]. After the aircraft is cleared for push-back, the taxi-out time to a runway threshold is generated. When the aircraft reaches the runway threshold, it enters a runway queue and is cleared for takeoff on an FCFS basis.

There are some research efforts to simulate more detailed aircraft motion on the airport surface and enable practical implementation of departure metering schemes. For instance, NASA developed a high-fidelity human-in-the-loop simulation model, and the simulation model is used to assess the Spot and Runway Departure Advisor tool [7], [10], [17]. Such a detailed simulation-based model can capture congestions and queues at all potential queuing locations such as taxiway merge locations. The queuing model used in this paper and discussed above has a limited capability to simulate potential queues on the airport surface. Indeed, the queuing model has queues only in the ramp area and the runway. However, the queuing model used in this paper enables faster simulations than detailed models, and it is capable of accurately estimating push-back and takeoff time distributions. The objective of this paper is to analyze the impact of gate assignment on departure metering, and the resolution of the queuing model is sufficient for the analysis.

B. Data Source

The queuing model is calibrated to LGA operations using 2009 data from Aviation System Performance Metrics (ASPM) provided by the Federal Aviation Administration (FAA). ASPM contains actual departure time, takeoff time, taxi-out time, tail number, runway configuration, etc. The data are categorized by departure runway. Frequently used runway configurations are given in Table I, and the layout of LGA is shown in Fig. 1. Most of the time, one runway is used for arrivals and another runway is used for departures. Table I shows that runway 13 served departures the most frequently. Precisely, runway 13 operated for 3456 h (39.5% of the year) and served 83143 push-backs (47.6% of push-backs that year). Therefore, the queuing model is calibrated with departures from runway 13.

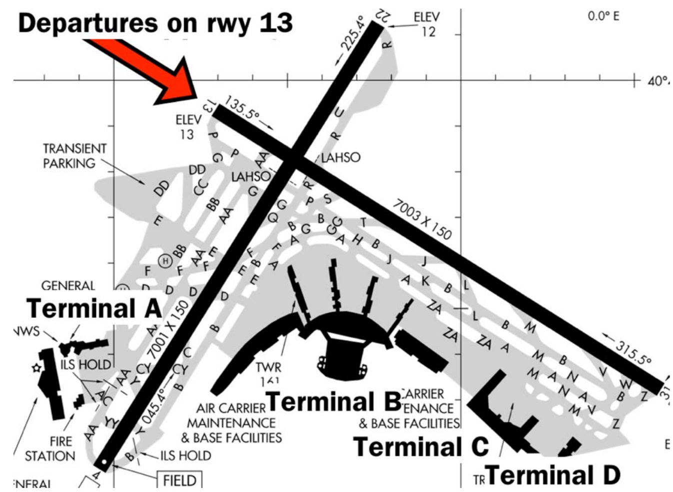

Fig. 1. Layout of LGA. All departures on runway 13 are modeled and arrivals are aggregated.

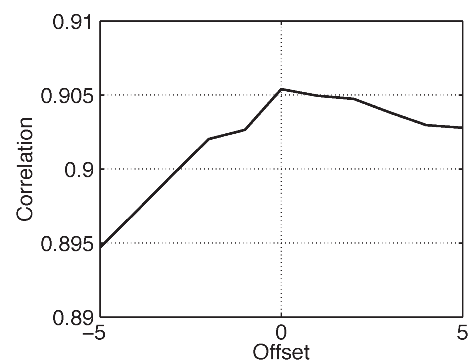

Fig. 2. Correlation between $N(t)$ and $T(t + \delta t)$: $N(t)$ best predicts $T(t)$.

C. Takeoff Model

As Shumsky has shown in [1], the takeoff rate is related to N, i.e., the number of aircraft on the airport surface. Let $N(t)$ be the number of taxi-out aircraft at time t and $T(t)$ be the average number of takeoffs per minute over the time periods $[t, t+9]$. Pujet *et al.* calculate the correlation between $N(t)$ and $T(t + \delta t)$ in order to find δt, where N predicts accurate T [5]. Fig. 2 shows that the maximum correlation between N and T occurs with $\delta t = 0$. Therefore, the number of taxi-out aircraft at an instant of time best predicts the number of takeoffs over the next 10 min. It is known that arrivals influence departure rates [11]. However, we neglect this effect in our study for the simplicity of analysis.

Fig. 3 shows the average and standard deviation of $T(t)$ according to $N(t)$. The vertical bars indicate the standard deviation of $T(t)$ for each $N(t)$. $T(t)$ and $N(t)$ are calculated by analyzing ASPM data. $T(t)$ increases with $N(t)$ until $N(t)$ becomes 15, which is N^*. When N is greater than or equal to N^*, the departure throughput is limited by the runway capacity. The runway capacity is obtained from $T(t)$ when $N(t)$ is in the range [15, 20]. The mean and standard deviation of takeoff rate are 0.5666 and 0.1234 aircraft/min, respectively. Fig. 3 is equivalent to the flow–density curve in the ground transportation literature [18]–[21]. Unlike road models in which throughput (flow) is limited by road characteristics such as jam

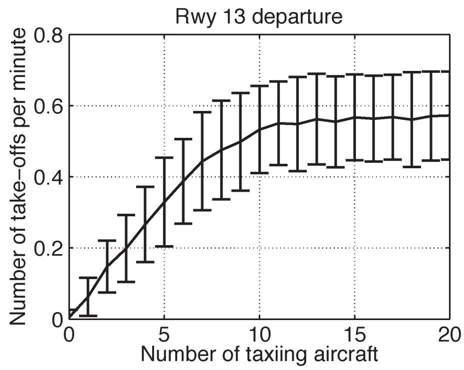

Fig. 3. $T(t)$ as a function of $N(t)$. The vertical bars indicate the standard deviation of $T(t)$ for each $N(t)$.

TABLE II
VARIABLES AND PARAMETERS OF THE TAKEOFF MODEL

Name	Value
c_1	0.525 aircraft/minute
c_2	1.025 aircraft/minute
c_3	0.025 aircraft/minute
p_1	0.3733
p_2	0.38

density and free-flow speed, airport throughput is limited by runway capacity only. In some extreme cases, airport throughput can be seen to decrease, as in the road models, at very high rates of airport surface occupancy. Such gridlock situations are, however, less common at airports than they are on congested road networks.

In order to capture the first and the second moments of $T(t)$, two variables (p_1 and p_2) are defined and three parameters (c_1, c_2, and c_3) are calculated based on values of the variables. A takeoff clearance is modeled as follows:

- c_1 aircraft per minute with probability p_1;
- c_2 aircraft per minute with probability p_2;
- c_3 aircraft per minute with probability $1 - p_1 - p_2$.

The proposed takeoff model simulates the number of takeoff clearances by three discrete numbers, i.e., c_1, c_2, and c_3. Then, the runway capacity is expressed as

$$\mu = c_1 p_1 + c_2 p_2 + c_3 (1 - p_1 - p_2) \tag{1}$$

$$\sigma = \sqrt{\frac{c_1^2 p_1 + c_2^2 p_2 + c_3^2 (1 - p_1 - p_2) - \mu^2}{10}}. \tag{2}$$

Therefore, the takeoff model captures the mean and standard deviation of $T(t)$ with p_1 and p_2, which are calculated by (1) and (2). The three parameters are explored in increments of 0.025 to find the best set of parameters that simulates the distribution of takeoff rate at $N = N^*$. The variables and parameters of the takeoff model are given in Table II, and Fig. 4 shows the distribution of takeoff rates from ASPM data and the takeoff model.

When the runway queue is not empty, the takeoff model randomly selects the current takeoff rate c according to p_1 and p_2. Thus, c is equal to c_1, c_2, or c_3 with probabilities p_1, p_2, or $1 - p_1 - p_2$, respectively. The current takeoff rate c is added to the previous takeoff rate, and the largest integer smaller than this cumulative sum of c is the maximum number of takeoff clearances at the current time step. Then, the actual number of takeoffs is subtracted from the cumulative sum of c. For example, suppose that the cumulative sum of c at the previous time step is 0.55, and the c at the current time step is 0.525. Then, the cumulative sum of c at the current time step becomes $0.55 + 0.525 = 1.075$, and one takeoff can be cleared at the current time step. Because there are aircraft in the runway queue, the takeoff model clears a takeoff. Then, the cumulative sum of c becomes $1.075 - 1 = 0.075$. Note that the takeoff model clears only an integer number of aircraft. The throughput of the airport departure model is sensitive to the takeoff model.

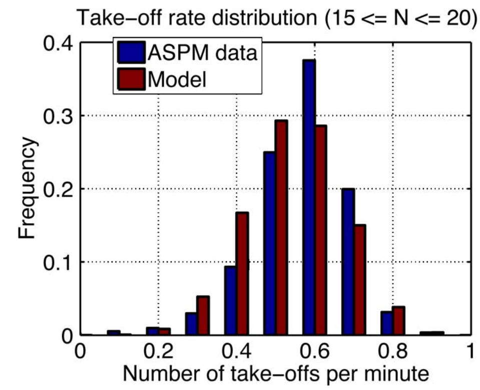

Fig. 4. Takeoff rate distribution at LGA. The takeoff model simulates the departure throughput well.

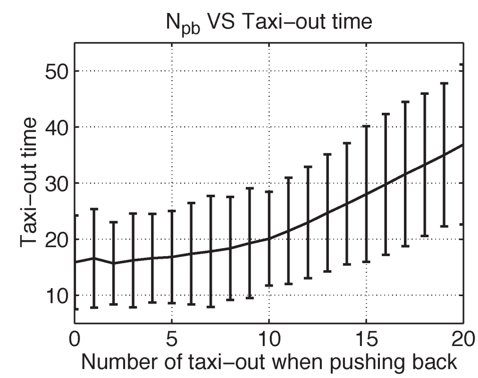

Fig. 5. Taxi-out time according to the number of taxi-out aircraft when an aircraft pushes back. The average taxi-out time does not increase until there are three to four taxi-out aircraft.

D. Taxi-Out Time Estimation

Taxi-out times in ASPM data are grouped by each terminal in LGA, i.e., terminals A, B, C, and D. Individual airlines tend to cluster their flights within a single terminal, and this terminal changes according to the airline. For instance, most flights of U.S. Airways use terminal C, and Delta Airlines flights use terminals A and D; terminals in LGA are indicated in Fig. 1. In order to get nominal taxi-out times, which are the taxiing times from a gate to a runway without a queuing delay on surface, taxi-out times are filtered by the number of taxi-out aircraft when an aircraft pushes back N_{pb}. Thus, N_{pb} indicates the number of departures that is on the way to the runway ahead of a pushing-back aircraft. Fig. 5 shows the means and the standard deviations of taxi-out time according to N_{pb}. The mean

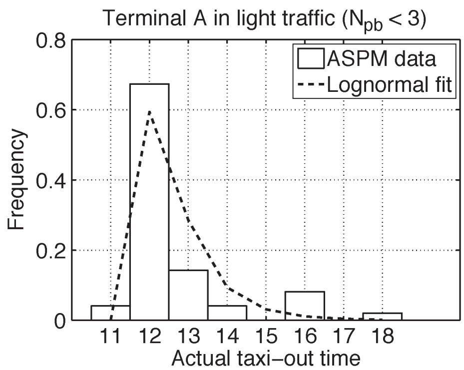

Fig. 6. Taxi-out time of Terminal A in light traffic (the number of taxi-out aircraft is fewer than three).

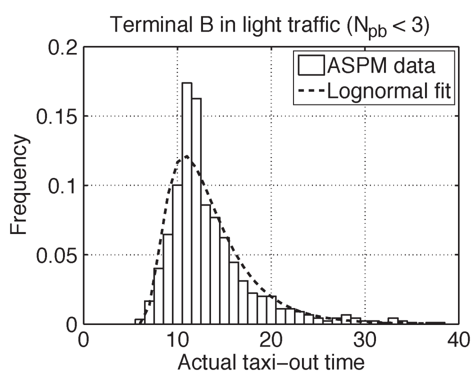

Fig. 7. Taxi-out time of Terminal B in light traffic (the number of taxi-out aircraft is fewer than three).

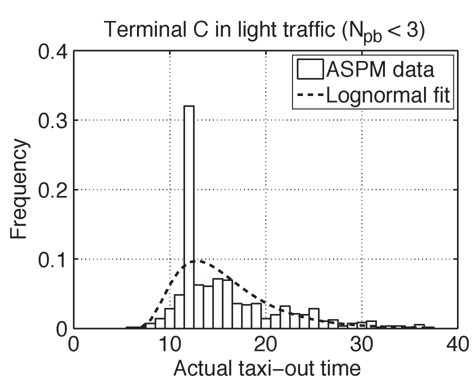

Fig. 8. Taxi-out time of Terminal C in light traffic (the number of taxi-out aircraft is fewer than three).

taxi-out time does not increase until N_{pb} becomes 3. Hence, it is assumed that there is light traffic on the airport surface and taxi out is unimpeded when $N_{\mathrm{pb}} < 3$. A lognormal distribution is used to model the nominal taxi-out time, and Figs. 6–9 show the taxi-out time of each terminal and their lognormal fits. Figs. 6 and 8 show an exceptionally high peak at 12 min as these terminals serve mostly small aircraft such as CRJ and ERJ. According to Simaiakis [22], this high peak is caused by a reporting issue of the ASPM data. Some airlines or aircraft do not participate to record their push-back (Out), takeoff (Off), landing (On), and arrival (In) times. For those flights, the taxi-out times are estimated using the median taxi-out time of the airport, which corresponds to the high peak.

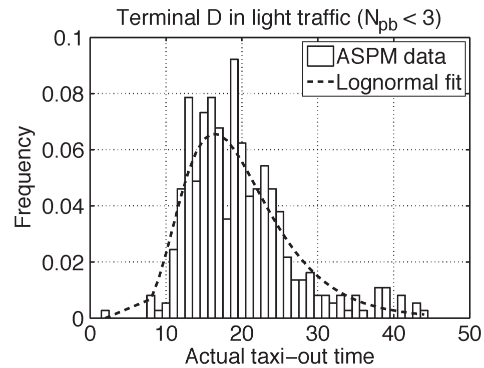

Fig. 9. Taxi-out time of Terminal D in light traffic (the number of taxi-out aircraft is fewer than three).

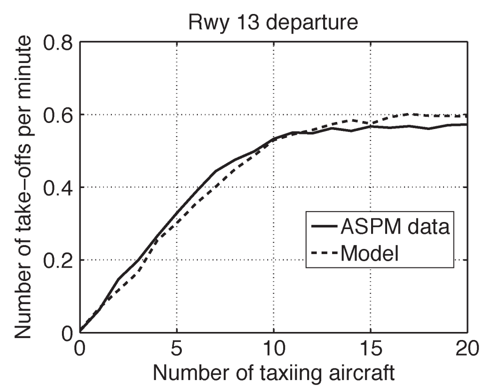

Fig. 10. Model validation: T versus N.

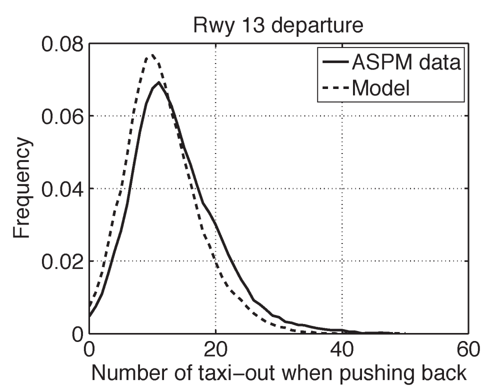

Fig. 11. Model validation: distribution of N_{pb}.

E. Model Validation

The calibrated departure model is validated with departures on runway 13 in 2009. Fig. 10 shows the graph of T versus N. The model reproduces the takeoff rate well. Fig. 11 shows the distribution of N_{pb}. Figs. 12–14 show the distribution of taxi-out times in light ($N_{\mathrm{pb}} < 3$), medium ($3 \leq N_{\mathrm{pb}} < 10$), and heavy ($N_{\mathrm{pb}} \geq 10$) traffic. The model reproduces every traffic situation except for a high peak at 12 min, which is caused by the ASPM reporting issue along with the high peaks in Figs. 6 and 8.

III. Airport Gate Assignment

If a departing aircraft is delayed at a gate and an arriving aircraft requests the gate, the arriving aircraft should wait until

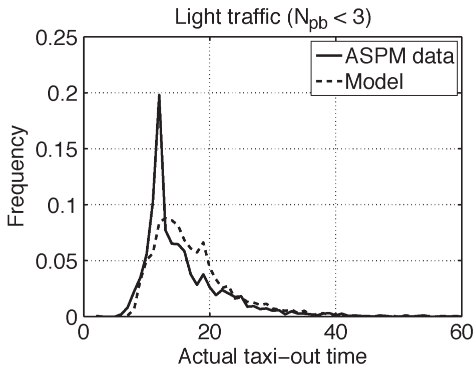

Fig. 12. Model validation: taxi-out time in light traffic.

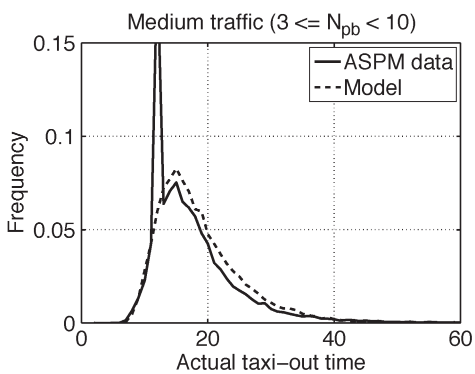

Fig. 13. Model validation: taxi-out time in medium traffic.

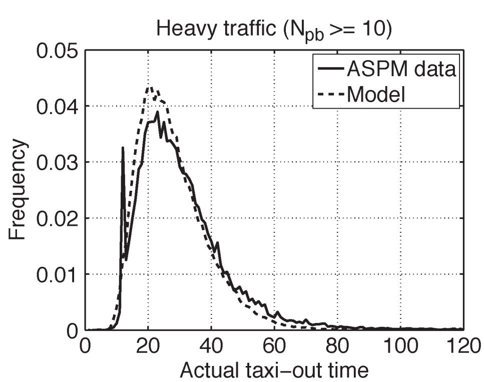

Fig. 14. Model validation: taxi-out time in heavy traffic.

the departing aircraft pushes back and the gate is cleared or be reassigned to another gate. This is known in the literature [23] as a gate conflict, and the duration of the overlap between the arrival time of the next aircraft and the departure time of the previous aircraft is known as a disturbance to the gate assignment. Fig. 15 illustrates a gate conflict and the corresponding overlap duration, where $act_a(i)$ is the actual arrival time of flight i, $act_d(i)$ is the actual departure time of flight i, $act_a(k)$ is the actual arrival time of flight k, and $act_d(k)$ is the actual departure time of flight k.

Since arrival and departure delays are uncertain, the expected overlap duration is numerically calculated with the probability distributions of the delays that are derived from ASPM data. First, probability distributions of departure and arrival delays are found for departure runway 13 of LGA in 2009. Then, the expected overlap duration is calculated $E[act_d(i) - act_a(k), act_d(i) > act_a(k)]$ when the scheduled arrival time of flight k is later than the scheduled departure time of flight i. Briefly speaking, the actual departure time act_d or the actual arrival time act_a is the sum of the scheduled departure or arrival time and departure/arrival delays. Because the scheduled times are fixed, $E[act_d(i) - act_a(k), act_d(i) > act_a(k)]$ is a function of the departure delay of flight i and the arrival delay of flight k. Details are given in [23]. The numerically calculated disturbance is fit to an exponential function $A \times B^x$, where x is the gate separation. Parameters A and B are 8 and 0.97 for LGA. Fig. 16 shows the numerically calculated value and the exponential fit. The exponential function is found to fit the numerically calculated value well. As shown in Fig. 16, the expected overlap duration decreases as the gate separation increases. Note that the expected overlap duration is only about 8 min when gate separation is zero. The duration is surprisingly small because early departures and late arrivals occur frequently. More details on the delay distributions are available in [23].

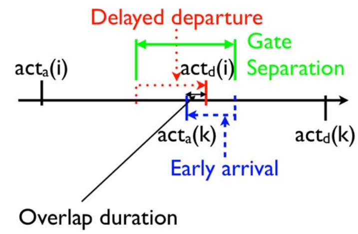

Fig. 15. Gate conflict and overlap duration. Flight i is scheduled to depart before flight k arrives at the gate, but flight k arrives before flight i pushes back.

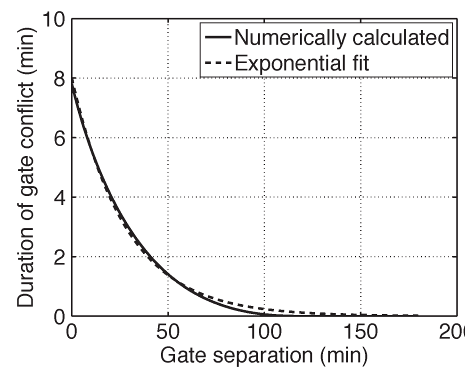

Fig. 16. Expected overlap duration in a function of gate separation. The expected duration of gate conflict exponentially decays as gate separation increases.

We write a formulation of the robust gate assignment problem as

$$\text{Minimize} \quad \sum_{i \in \mathcal{F}} \sum_{k \in \mathcal{F},\, k > i} A \times B^{\text{sep}(i,k)} \sum_{j \in \mathcal{G}} x_{ij}\, x_{kj} \tag{3}$$

$$\text{subject to} \quad \sum_{j \in \mathcal{G}} x_{ij} = 1, \qquad \forall\, i \in \mathcal{F} \tag{4}$$

$$\left(t_i^{\text{out}} - t_k^{\text{in}} + t^{\text{buff}}\right)\left(t_k^{\text{out}} - t_i^{\text{in}} + t^{\text{buff}}\right) \le M(2 - x_{ij} - x_{kj})$$
$$i \ne k, \qquad \forall\, i,\ k \in \mathcal{F}, \qquad \forall\, j \in \mathcal{G} \tag{5}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall\, i \in \mathcal{F}, \qquad \forall\, j \in \mathcal{G} \tag{6}$$

where

$$x_{ij} = \begin{cases} 1 & \text{if } f_i \text{ is assigned to } g_j \\ 0 & \text{otherwise} \end{cases}$$

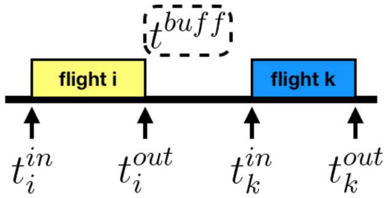

Fig. 17. Illustrative example of sufficient gate separation.

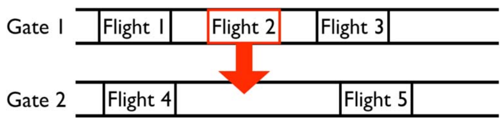

Fig. 18. Insert Move switches an aircraft's gate assignment to another.

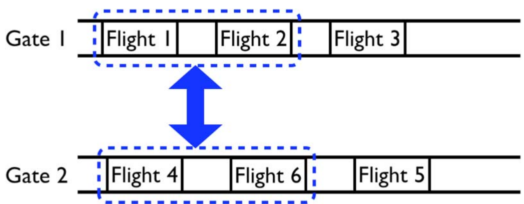

Fig. 19. Interval Exchange Move swaps two groups of gate assignments.

where $\mathcal{F}$ is a set of flights, $\mathcal{G}$ is a set of gates, $\text{sep}(i, k)$ is the gate separation of aircraft i and k, and M is an arbitrarily large number. x_{ij} is a decision variable of the optimization problem and has a value of 1 if aircraft i is compatible with and is assigned to gate j, and 0 otherwise; some gates are not capable to serve certain types of aircraft. The first constraint (4) requires every aircraft to be assigned to a single gate, and the second constraint (5) enforces gate separation between every pair of aircraft to be larger than a certain minimum, which is t^{buff}. For instance, flights i and k are assigned to the same gate, and their gate occupancy times are shown in Fig. 17. The gate separation of two flights, which is $t_k^{\text{in}}–t_i^{\text{out}}$, is greater than t^{buff}. Hence, the given assignment is feasible with respect to the second constraint (5).

The robust gate assignment problem is to minimize the total expected overlap duration. The problem is solved by Tabu Search (TS), which we have found to be an efficient method for solving gate assignment problems [23], [24]. TS utilizes the two types of neighborhood search moves shown in Figs. 18 and 19. "Insert Move" switches the assigned gate of an aircraft to another gate, and "Interval Exchange Move" swaps the assigned gate of a group of aircraft with that of another group of aircraft. Details are given in [23] and [24].

IV. Results

The current gate assignment and a robust gate assignment are used to analyze the impact of gate assignment on departure metering. The current gate assignment for May 10–14, 2012, is obtained from the website (www.flightstats.com). The robust gate assignment is based on scheduled flights because airport gates are assigned prior to the actual operation day.

The available flight schedules are separated into departures and arrivals, but an arrival and a departure sharing the same aircraft should be assigned to the same gate to eliminate any cost caused by towing the aircraft from one gate to another. Therefore, a departure is paired with an arrival by comparing the current gate assignment and the equipment type of each flight. It is frequently found in the current gate assignment that two arrivals use a gate consecutively and the gate is used for two consecutive departures. It is assumed that the first arrival is towed to somewhere else after it arrives, the second arrival arrives and departs, and then the first arrival is towed back to the gate for departure. In such a case, the corresponding arrival and departure are considered as a single arrival and a single departure that are not paired.

Each airline can use a subset of gates in LGA. For instance, US Airways uses gates mostly located in terminal C. This airline–gate compatibility constrains the robust gate assignment problem. Most airlines use gates in a single terminal, but a few airlines have gates in multiple terminals. For instance, Delta Airlines also operates gates in terminals A and D. In 2013, Delta Airlines began to use gates in terminal C. The data used in this paper do not reflect this recent change in LGA.

Table III compares gate separations of the current gate assignment with those of the robust gate assignment. It is shown that the robust gate assignment makes the average gate separation longer than the current gate assignment does. In addition, smaller standard deviation with the robust gate assignment indicates that the distribution of gate separation is less dispersed.

TABLE III
Comparison of Gate Separations

	Current Gate Assignment	Robust Gate Assignment
Mean Gate Separation	94 min	98.1 min
Std Gate Separation	155.7 min	123.3 min

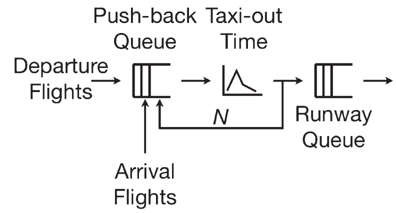

Fig. 20. Simulation structure.

A. Simulation Model

The current gate assignment and the robust gate assignment are simulated using the airport departure model. The simulation structure is given in Fig. 20. When a departure is ready to push back, it enters the push-back queue. A push-back is cleared FCFS, but if an arrival requests an occupied gate (gate conflict), the departure occupying the gate is cleared with the highest priority. When departure metering is active, push-back is not cleared until N is below N^{ctrl}. After the push-back, a taxi-out time is randomly generated according to the departure terminal and the aircraft enters the runway queue. From the runway queue, a takeoff is cleared FCFS.

The simulation takes the actual departure and arrival times of the selected period as inputs. Note that gates are assigned based on the scheduled departure and arrival times. All the arrivals

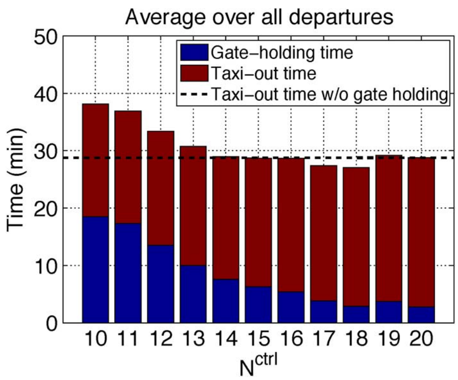

Fig. 21. Average gate-holding times and taxi-out times for the current gate assignment at LGA. The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 14 are similar to the average taxi-out time without departure metering.

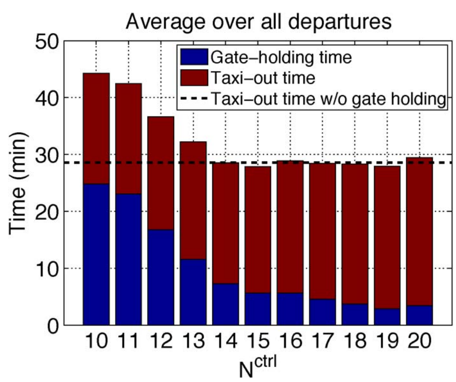

Fig. 22. Average gate-holding times and taxi-out times for the robust gate assignment at LGA. Like Fig. 21, the sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 14 are similar to the average taxi-out time without departure metering.

reach gates at actual arrival times, and all the departures enter the push-back queue at actual departure times. The simulation runs 15 times and is averaged.

B. Relationship Between Taxi-Out Times, Gate-Holding Times, and N^{ctrl}

Taxi-out times, gate-holding times, and N^{ctrl} are closely related. As N^{ctrl} increases, more departures are cleared to push back without metering. Hence, the airport surface becomes more congested, and taxi-out times are likely to increase. On the other hand, when N^{ctrl} is low, many departures are held at the gates, but taxiing aircraft can taxi out to the runway with fewer taxi delays. Figs. 21 and 22 show average gate-holding times and taxi-out times for the current gate assignment and the robust gate assignment with N^{ctrl} varying from 10 to 20. In order to compare taxi-out time savings with gate-holding time on the same scale, the gate-holding times are averaged over the whole set of departures not only the gate-held departures. As predicted, gate-holding times decrease and taxi-out times increase as N^{ctrl} increases. In addition, the sum of gate-holding time and taxi-out time decreases as N^{ctrl} increases and remains constant for N^{ctrl} equal to or greater than 14. Note that the average taxi-out time without departure metering is similar to the sums of gate-holding times and taxi-out times for N^{ctrl} equal to or greater than 14. This means that some taxi-out times are transferred to gate-holding times by departure metering. Then, gate-held departures can stay at gates without turning on their engines, and fuel consumption and emissions are reduced and, possibly, crew costs also.

TABLE IV
IMPACT OF GATE ASSIGNMENT ON DEPARTURE METERING AT LGA

Gate Assignment	Current		Robust	
Departure Metering ($N^{\mathrm{ctrl}} = 14$)	No	Yes	No	Yes
Number of Gate Conflicts	59	215.1	12.9	107.6
Number of Gate-held Departures	0	1267.7	0	1315.1
Mean Gate-held Times	0 min	12.6 min	0 min	13.3 min
Mean Taxi-out Times	29.4 min	21.5 min	28.4 min	21.3 min

C. Impact of Gate Assignment on Departure Metering

We analyze the impact of gate assignment on departure metering. Table IV compares the impacts of two gate assignments on departure metering. The variable N^{ctrl} is set to 14 with Figs. 21 and 22. With the current gate assignment, departure metering increases the number of occurrences of gate conflict over three times compared to no departure metering, and more than half of the departures (1267.7 out of 2409) are held at gates for 12.6 min on average. Note that the mean gate-held time in Table IV is averaged over gate-held departures (1267.7 departures) in order to show the actual duration of gate holding times experienced by gate-held departures, as opposed to Figs. 21 and 22 where average gate-holding time is computed with every departure, and the mean taxi-out time is averaged over the whole departures (2409 departures). Therefore, the reduction of taxi-out time from departure metering (7.9 min) is smaller than the mean gate-held time (12.6 min). With the robust gate assignment, 1315.1 out of 2409 departures are held at gates for 13.3 min on average over the gate-held departures. The robust gate assignment induces fewer gate conflicts than the current gate assignment, whether or not departure metering is used, as given in Table IV. The fewer gate conflicts coming from the robust gate assignment are due to the longer mean gate separation, as shown in Table III. Specifically, the robust gate assignment reduces the occurrence of gate conflicts by 78% compared to the current gate assignment when departure metering is active; it reduces the occurrence of gate conflicts by 50% when departure metering is inactive. This demonstrates that the robust gate assignment helps airlines and air navigation service providers reap the benefits of departure metering because it leads to fewer disturbances to the gate assignment. When departure metering is active, departures are released from gates (cleared to push back) prior to an optimum time if the gates are requested by arrivals, and early release is expected to happen more with the current gate assignment as indicated by the number of gate conflicts. Early gate release can induce an increase of taxi-out times. However, the average taxi-out time with the current gate assignment and active departure metering is just 0.2 min longer than that with the robust gate assignment and active departure metering. This number is somewhat smaller than expected. A possible explanation is that most gate-held departures are released at optimum times without being constrained by gate conflict. As given in Table IV, the ratios of the number of gate conflicts to the number of gate-held

TABLE V
FREQUENTLY USED RUNWAYS FOR DEPARTURE AT A U.S. HUB AIRPORT

Runways	% of Push-backs	
Configuration 1	40.4 % (VFR)	8.5 % (IFR)
8R, 9L	26.6 % (VFR)	12.8 % (IFR)

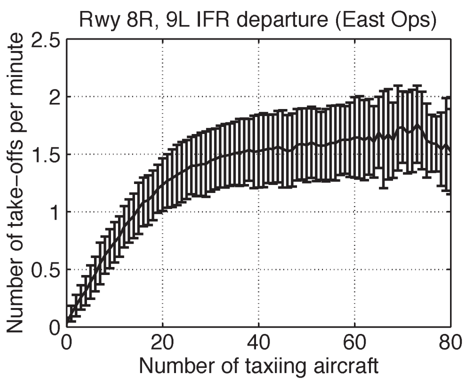

Fig. 23. $T(t)$ as a function of $N(t)$. The vertical bars indicate the standard deviation of $T(t)$ for each $N(t)$.

departures are 0.17 for the current gate assignment and 0.08 for the robust gate assignment. It means that 83% of gate-held departures with the current gate assignment and 92% of those with the robust gate assignment are released without gate conflict. In addition, Table III tells that mean gate separation (94 min for the current gate assignment and 98.1 min for the robust gate assignment) is much longer than the mean gate-held times (12.6 min for the current gate assignment and 13.3 min for the robust gate assignment), which supports this explanation too.

D. Expansion of the Model to Another Airport

The queuing model is applied to another airport, which is one of the busiest hub airports in the U.S. Two airlines dominate the traffic of the airport.[1] Carrier A operates 71.2% of operations, and carrier B operates 16.6% of operations. There are five runways in the airport, and two of them accommodate departures most of the time. The most frequently used runways for departure in 2009 are given in Table V. The meteorological condition of the airport is categorized by Visual Flight Rules (VFR) and Instrument Flight Rules (IFR). When the airport is under IFR, the runway throughput is reduced and the airport surface becomes more congested. Hence, the benefit of departure metering is likely to increase under IFR.

The queuing model is calibrated with departures from 8R and 9L runways under IFR. The corresponding departures account for 12.8% of departures in 2009. The mean and standard deviation of the airport throughput $T(t)$ versus $N(t)$ are shown in Fig. 23. Similar to Fig. 3, $T(t)$ increases with $N(t)$ and is saturated when $N(t)$ is larger than a certain number. It is shown that $T(t)$ drops when $N(t)$ is higher than 70. This drop might indicate gridlock and correspond to what is observed in the ground transportation literature [18], [19] when traffic is very dense: Traffic density then replaces runway capacity as the factor that limits airport throughput. The takeoff model is

[1]Names of the airport and airlines are withheld to protect the airlines' data.

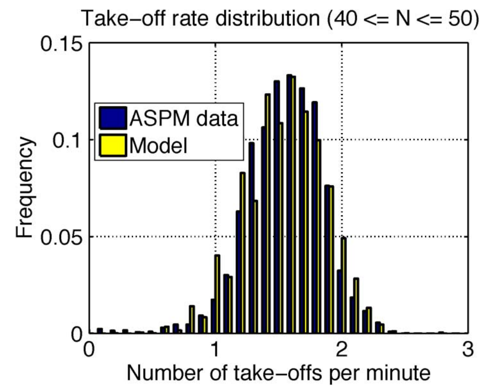

Fig. 24. Takeoff rate distribution at a U.S. hub airport. The takeoff model simulates the departure throughput well.

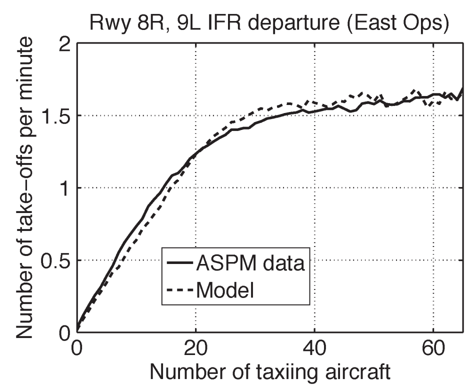

Fig. 25. Model validation: T versus N.

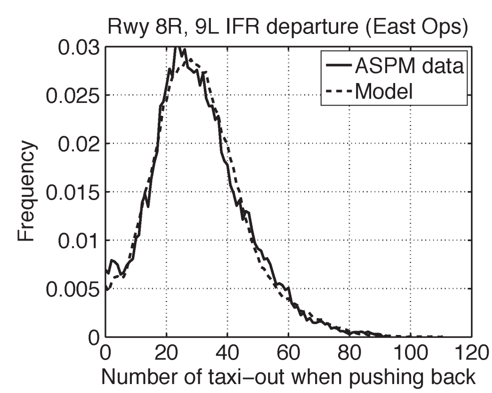

Fig. 26. Model validation: distribution of N_{pb}.

calibrated from $T(t)$ when $N(t)$ is in the range of [40, 50], and it is shown in Fig. 24.

The T versus N curve is given in Fig. 25. It is shown that the model reproduces the saturation of the departure throughput well. In addition, the model simulates surface congestion, as shown in Fig. 26. N_{pb}, which is the number of taxi-out aircraft when an aircraft pushes back, indicates how airport surface is congested when each aircraft leaves the gate. In Figs. 25 and 26, the model is successful at simulating departure operations in every traffic situation.

Two gate assignments are assessed, i.e., the current gate assignment and the robust gate assignment. The current gate assignment is obtained from carrier A, and the robust gate assignment is given in [25]. The relationship between taxi-out

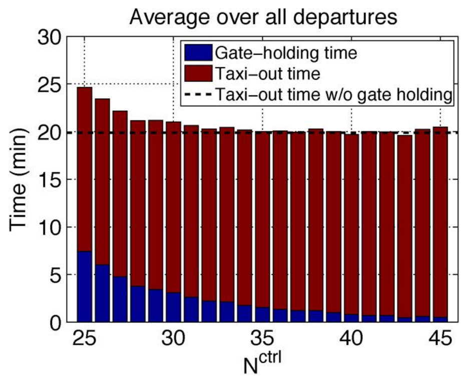

Fig. 27. Average gate-holding times and taxi-out times for the current gate assignment at a U.S. hub airport. The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 33 are similar to the average taxi-out time without departure metering.

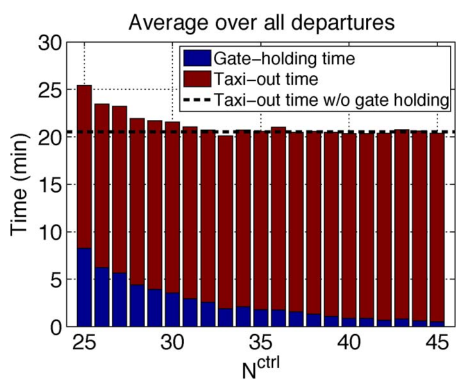

Fig. 28. Average gate-holding times and taxi-out times for the robust gate assignment at a U.S. hub airport. The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 33 are similar to the average taxi-out time without departure metering.

TABLE VI
IMPACT OF GATE ASSIGNMENT ON DEPARTURE METERING AT A U.S. HUB AIRPORT

Gate Assignment	Current		Robust	
Departure Metering ($N^{\mathrm{ctrl}} = 33$)	No	Yes	No	Yes
Number of Gate Conflicts	233	253.3	77	102.7
Number of Gate-held Departures	0	306.2	0	363.3
Mean Gate-held Times	0 min	7.9 min	0 min	7 min
Mean Taxi-out Times	20.1 min	18.2 min	20.7 min	18.3 min

times, gate-holding times, and N^{ctrl} is illustrated in Figs. 27 and 28. From the figures, N^{ctrl} is set to 33.

Table VI compares the impact of the current gate assignment on departure metering with that of the robust gate assignment. More than half of gate conflicts are eliminated by the robust gate assignment when departure metering is active. For both gate assignments, it is shown that the average reduction of taxi-out times is about 2 min for all flights by holding some departures at their gates for 7–8 min. The results in Table VI are similar to those in Table IV, but the benefit is smaller. The hub airport utilizes two runways for departures and three runways for arrivals and has a large taxiway system as opposed to LGA with one runway for departures and a small taxiway system. Hence, the hub airport is capable of handling more traffic on the airport surface than LGA, and the saturation of departure throughput occurs for large N. As a result, about one-fourth or one-third of the departures are held at the gates,

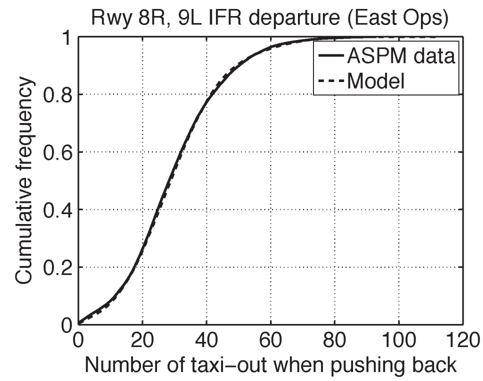

Fig. 29. Cumulative distribution of N_{pb}. About 70%–75% of the departures are cleared to push back when the number of taxi-out aircraft is fewer than 40, which corresponds to the throughput saturation point.

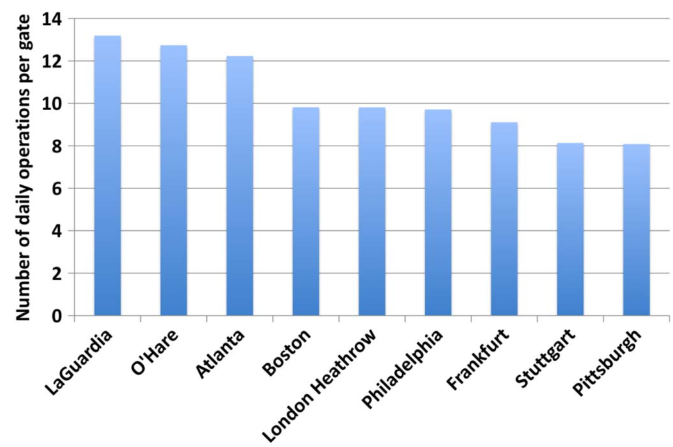

Fig. 30. Number of daily operations per gate for some busy international airports. Higher number indicates higher probability of gate conflicts.

as compared with more than half the departures held at the gates at LGA. Hence, about 70%–75% of the departures at the hub airport are cleared to push back before the runways are saturated ($N_{\mathrm{pb}} < 40$), as shown in Fig. 29, and it is why the reduction of taxi-out times is smaller than LGA.

Fig. 30 shows the number of daily operations per gate for some busy airports in the world. It is indicated that gates of LGA are busier than those of U.S. major hub airports such as Hartsfield–Jackson Atlanta Airport and Chicago O'Hare Airport. Considering the fact that a single runway is used for departures at LGA and multiple runways are used for departures at U.S. major hub airports, the runway throughput of LGA is lower than those of U.S. major hub airports. Lower runway throughput and higher gate utilization at LGA indicate that departure metering would cause more gate conflicts at LGA, and the benefit of the robust gate assignment is relatively small for the hub airport of interest. However, it does not imply that all hub airports do not enjoy the benefits of the robust gate assignment and departure metering. Many airports including Boston, London Heathrow, and Frankfurt welcome very large aircraft, which require longer turn-around times; hence, the gates are still extremely busy. For example, Boeing 777 needs turn-around times of 70 min for domestic flights and 120 min for international flights. On the other hand, Boeing 737 needs the turn-around time of 40 min. Hence, although the number of operations per gate is small, the gates can still be busy and the benefits of the robust gate assignment and departure metering would be big.

V. Conclusion

This paper has presented an analysis of the impact of gate assignment on departure metering. In order to simulate the airport departure process, a queuing model is proposed, consisting of a push-back queue, taxi-out time estimates, and a runway queue. The model is validated and reproduces airport departure throughput close to the data. Because the performance of departure metering relies on gate separations, a robust gate assignment is introduced.

The results show that departure metering shifts some taxi-out times to gate delays, and it causes gate conflicts between the gate-held departures and arrivals. The robust gate assignment reduces the occurrence of gate conflicts under departure metering by maximizing gate separations. Moreover, the benefits of the robust gate assignment would be greater when arrival rate is high. In this paper, the influence of arrival rate on takeoff rate is neglected, but indeed high arrival rate reduces takeoff rate, which increases gate holding. Thus, more departures tend to be held at their gates exactly when there is more arrival demand for the gates, which would cause more gate conflicts. Therefore, this paper provides lower bounds on the performance under smart gate assignment. In the future, this destabilizing term due to arrivals will be addressed.

Future work will address the impact of the changed gate assignments on passengers. Most passengers at hub airports are there to transfer their flights as opposed to LGA. Therefore, the change of gate assignments influences passengers' transit time at the airport terminal. In particular, the consequence will be significant to transfer passengers because their transit routes depend entirely on the gate assignments. In addition, future work will consider geometrical characteristics of the airport that would influence departure operations. For instance, if there is a single taxi lane shared between departures and arrivals on the ramp, a push-back needs to be cleared much earlier than when the following arrival reaches the gate.

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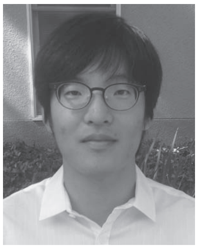

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