# FAST-TIME SIMULATIONS OF DETROIT AIRPORT OPERATIONS FOR EVALUATING PERFORMANCE IN THE PRESENCE OF UNCERTAINTIES

*Hanbong Lee and Hamsa Balakrishnan, Massachusetts Institute of Technology, Cambridge, MA*

## Abstract

The airport environment is a very uncertain environment, primarily due to large variations in performance and efficiency. While the presence of uncertainties and their influence on airport operations has been recognized, their characteristics and impacts have not been studied in detail. This paper investigates the impacts of uncertainty on airport performance through fast-time simulations using SIMMOD. Various uncertainty sources, such as pushback times, runway exit times, taxi speeds, and runway separation times, are evaluated with actual flight schedules at Detroit International Airport. The simulations show that the ground delay increases with an increase in uncertainty level for most scenarios. The paper also shows that surface traffic optimization based on a deterministic model can still be valid in the presence of certain types of uncertainties.

## Introduction

There are considerable levels of uncertainty in different elements of airport operations that can affect performance. These sources of uncertainty include differences in flight checklists, pushback processes, taxi speeds, pilot-controller communications, and so on. These factors lead to large variations in pushback times, taxi times, takeoff times, and departure sequences. As a result, the actual movements of flights can be significantly different from the trajectories predicted or recommended by the optimization models, making it difficult for air traffic controllers to guide flights as planned.

Several researchers studying airport system management and planning have recognized the presence of uncertainty in airport operations and its importance [1-6]. Previous work has focused on the design of a stochastic algorithm for airport surface operations, but assumed known sources of uncertainty for arrivals and departures [1]. A modeling architecture to handle uncertainties that arise in communication, navigation and surveillance was implemented using a fast-time simulation of the National Airspace System (NAS) [2]. A basic method to quantify taxi speed distributions was previously proposed for the robust taxi flow optimization [3]. The variability in movements of taxiing aircraft due to uncertainties has been analyzed with actual flight data as part of research on surface trajectory-based operations [4, 5 ,6].

The presence of uncertainties has also made it difficult to develop accurate and efficient algorithms for airport surface traffic planning. Several queuing models and regression techniques have been proposed for the prediction of taxi-out times [7, 8], but most optimization approaches to aircraft taxi scheduling are based on the deterministic models [9]. The use of stochastic optimization models has been limited due to the difficulty of formulation and the computational cost, but also due to a lack of quantification of the effects of uncertainty [1, 10].

Fast-time simulations could be used instead of actual surveillance data to analyze the impacts of uncertainty on surface operations. Simulation tools have been previously developed for modeling airport operations [11]. Microscopic simulation models like SIMMOD have been enhanced to simulate the movement of individual aircraft both at airports and in the airspace with a fair degree of detail [12]. They can also simulate certain stochastic processes by using random variables to express the uncertainty in airport operations. In this paper, a fast-time air traffic simulation tool (SIMMOD) is used to generate various uncertainty scenarios, and to investigate the resultant impacts on airport performance.

This paper first identifies the uncertain factors that influence airport performance, such as taxi time, wait time on taxiways, and runway throughput. Next, a simulation model representing the physical layout and operational rules at Detroit airport is described. This model will be used for evaluating the effects of key uncertainty factors using actual flight schedules. In the last section, the results of the Monte Carlo simulations using SIMMOD are used to show how each uncertainty factor impacts ground delay, which is defined as the difference between the actual and the unimpeded taxi times.

## Uncertainty in Airport Operations

Uncertain elements of airport surface operations include actual pushback times of departures, actual landing times of arrivals, taxi speeds of aircraft, holding times on the taxiway and in departure queues, roll distances, and actual separation times between consecutive flights over the runway, etc.

From surface surveillance data, the uncertainty can be measured as the variability in pushback times, departure sequence, takeoff/landing times, times at each intersection on surface, time at departure/arrival fix, and departure/arrival spacing [1]. The analysis of surface traffic data at Dallas/Fort Worth International Airport (DFW) using the Surface Operations Data Analysis and Adaptation (SODAA) tool showed the impact of uncertainty on surface operations [4, 5, 6]. This research identified some of the sources of variability in current surface operations, specifically runway occupancy times, taxi turn times, runway crossing times, and taxi paths actually used.

In this paper, several uncertainty factors in airport operations are studied using a stochastic model in SIMMOD in order to investigate their impact on ground delays and taxi times, including:

- Actual pushback times of departures, which are random perturbations of the given flight schedule using gate service (occupancy) times in SIMMOD.
- Varying taxiway entrance times of arrivals, which can be varied by landing roll distances in SIMMOD.
- Different taxi speeds on the taxiway and the ramp areas depending on the flights.
- Uniformly distributed separation times between takeoffs, determined by the in-trail separation multiplier in SIMMOD.

These uncertainty elements can be modeled by fast-time computer simulation tools using random variables at microscopic level. In the next section, we describe the simulation modeling approach and the flight schedule scenarios used in the case studies.

## Fast-Time Simulation Environment

### *SIMMOD*

SIMMOD is a well-known airspace and airfield simulation tool, capable of calculating airport capacity, flight travel time, delay, and fuel consumption [13, 14]. This tool can build airspace and airport models from input data, and simulate detailed traffic flows. The inputs include aircraft, airspace, airfield, and event information, ATC policies and procedures, physical layouts of the airport and airspace, and flight schedules. SIMMOD provides detailed simulated outputs for each flight, and the corresponding statistics. Output data include aircraft travel times, traffic flows at specific points, capacities, delays and their reasons, and fuel consumption. This simulation tool can also visualize how aircraft move and interact with other flights at airports or in airspace. The SIMMOD environment has been validated using a number of airport case studies. It has been used to plan potential improvements by simulating alternatives in operations, technologies, or facilities. Examples of case studies include airport layout changes, proposed changes to runway or airfield operations, terminal traffic estimation, runway occupancy time estimation, and multi-airport interactions in the New York area [15, 16, 17].

SIMMOD supports stochastic processes through repeated runs with random seeds. In order to generate realistic and statistically significant results from given inputs, it is necessary to run a sufficient number of trials with randomized variables for a single data set. The random variables available in airport models include gate occupancy times, injection times of multiple arrivals and departures, takeoff and landing roll distances, in-trail separation multiplier to vary separation requirements, lateness of flights, pushback or power-back times, runway crossing start-up times, and slot times [18, 19].

Monte Carlo simulations using SIMMOD can be used to assess the impacts of uncertainty on select performance metrics, and to study the effects of uncertain factors in airport operations on the ground delay. The analysis of variability through fast-time simulations is complementary to analyses using limited observation data from SODAA, because of the ease of flight schedule generation and adaptation in SIMMOD.

### *Airfield Model for DTW*

For the fast-time simulations, an airfield model representing the airport layout and the operational parameters is first created in SIMMOD. Detroit Metropolitan Wayne County Airport (DTW) is chosen for the case studies about uncertainty effects presented in this paper. The airport has six runways and three terminals (McNamara, Smith, and Berry), as shown in Figure 1.

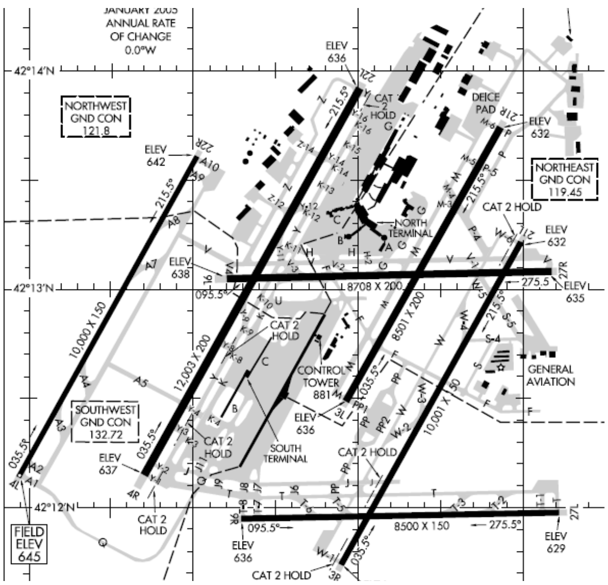


**Figure 1. DTW Airport Layout**

The basic SIMMOD model for DTW is based on a node-link network for the airport surface, consisting of 715 nodes that represent significant control points on the airport surface and 863 links that connect adjacent nodes. SIMMOD can import the coordinates of nodes and the connectivity information of links in Google Earth KML format. Some nodes and links for fixes and air routes connected to the runways are also added to represent the airspace around the airport.

Additional model inputs include data on runways, taxiways, gates, departure queue areas and their capacities, taxiway operation conditions (link capacities, overtaking rules, taxi speeds, and directionality), gate operation rules (capacity, blocking state, and airline assignments), and taxi path assignments. Aircraft follow prescribed paths that are represented by strings of links on the network. Based on surface surveillance data from DTW, taxi speed values are set to 3, 7, and 18 knots in the gate areas, ramp areas, and taxiways, respectively. It is assumed that all flights move at these speeds, irrespective of aircraft type.

The model also requires inputs about runway procedures such as separation distances, time intervals, approach speeds and occupancy times. The separation time requirements between successive departures are shown in Table 1, and depend on the weight classes of leading and trailing aircraft.

**Table 1. Minimum Separation Time (in Seconds) between Takeoffs**

| Leading Aircraft | Trailing Aircraft | | | |
|---|---|---|---|---|
| | **Heavy** | **B757** | **Large** | **Small** |
| Heavy | 120 | 120 | 120 | 120 |
| B757 | 90 | 90 | 90 | 90 |
| Large | 60 | 60 | 60 | 60 |
| Small | 60 | 60 | 60 | 60 |

Figure 2 shows the resultant model for DTW constructed in SIMMOD representing the airport surface, gates in terminal buildings, and surrounding airspace. This model is used for the various simulation scenarios presented in this paper. The operational parameters defined in the model also remain the same, except for the random variables that are varied in each experiment.

The flight schedule data, including airlines, flight numbers, aircraft types, origin/destination airports, airspace routes, runways, gates, and taxi paths, are recorded into the event file in SIMMOD. Pushback times for departures and landing times for arrivals are recorded as the event time when the flights appear in the simulation.

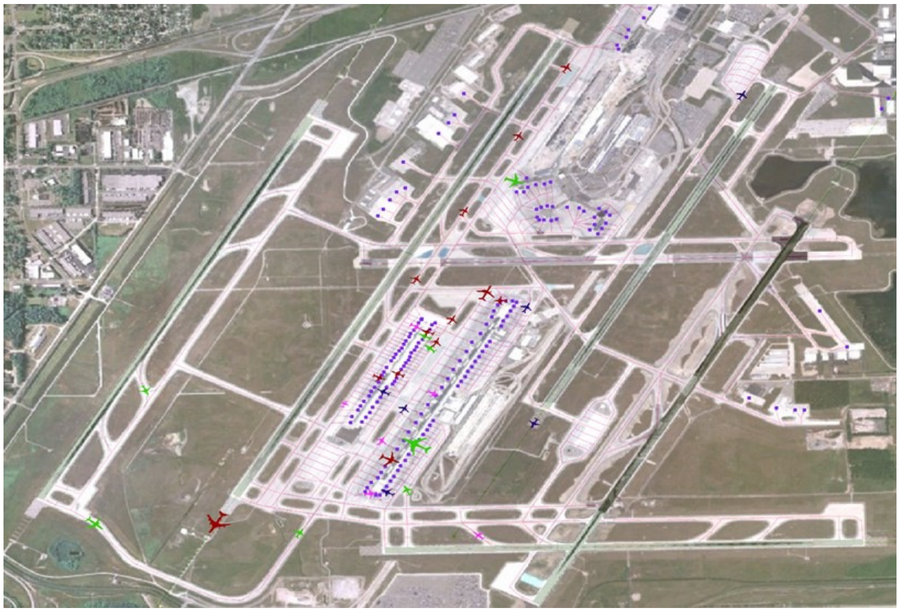

**Figure 2. SIMMOD Airfield Model for DTW**

### *Simulation Model Validation*

The simulation model described above is validated with actual flight data from DTW on 8/1/2007. A total of 1291 flight movements were observed at this airport between 6AM and midnight, consisting of 654 departures and 637 arrivals. The runway configuration was (22R, 27L | 21R, 22L) during the whole day, which was also the most frequently used configuration at DTW in 2007. The flight schedule was simulated in SIMMOD under the same operating conditions, and the resultant travel times on the surface, including the unimpeded taxi time and ground delay for each flight, were analyzed.

Figure 3 shows the average taxi-out times from the SIMMOD simulation and the surveillance data for each 5-min interval during the day. The two curves are similar for low traffic levels, like the early morning periods. At most times, however, there is a significant gap between the simulated and actual values. As the number of flights moving on the ground increases, the gap becomes larger. No uncertainty was taken into account in this SIMMOD simulation, which neglected the effect of uncertainty on travel times and the increased interactions between flights in high traffic density situations. Other causes for the difference between the simulated and observed values may include measurement errors and missing records in the surveillance data.

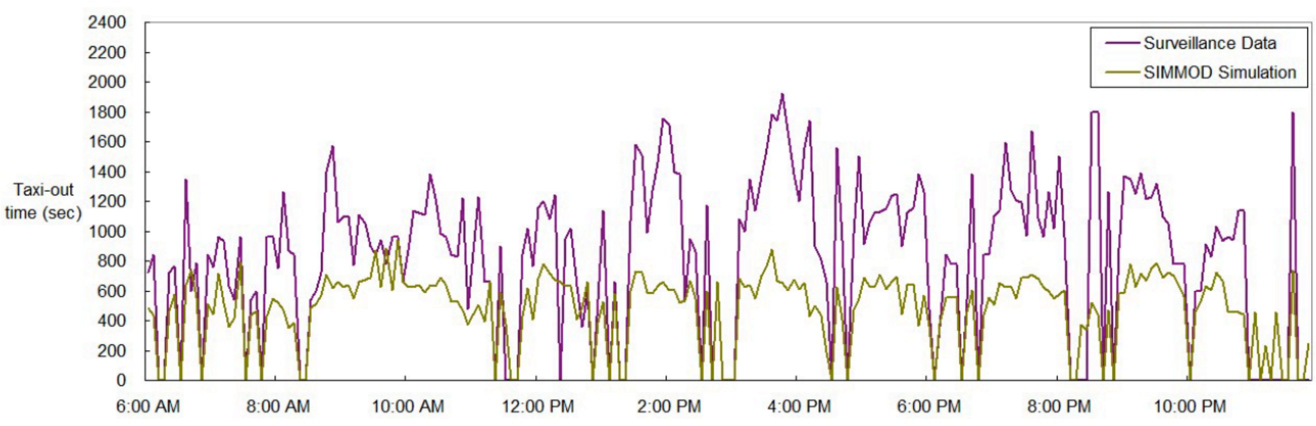


**Figure 3. Taxi-out Time Comparison between SIMMOD Simulations and Surveillance Data**

To validate simulation parameters such as taxi speeds and routes, the unimpeded taxi-out times from the SIMMOD simulation and a queueing model are compared. The unimpeded taxi time for departures can be estimated by the linear regression method used in the queueing model for airport departure process [7]. This method was validated for several major airports [20] and applied to DTW airport considering airlines, gates, runways, and weather conditions [21]. As shown in Figure 4, the unimpeded taxi-out time curves from the queuing model and the SIMMOD simulation are very similar.

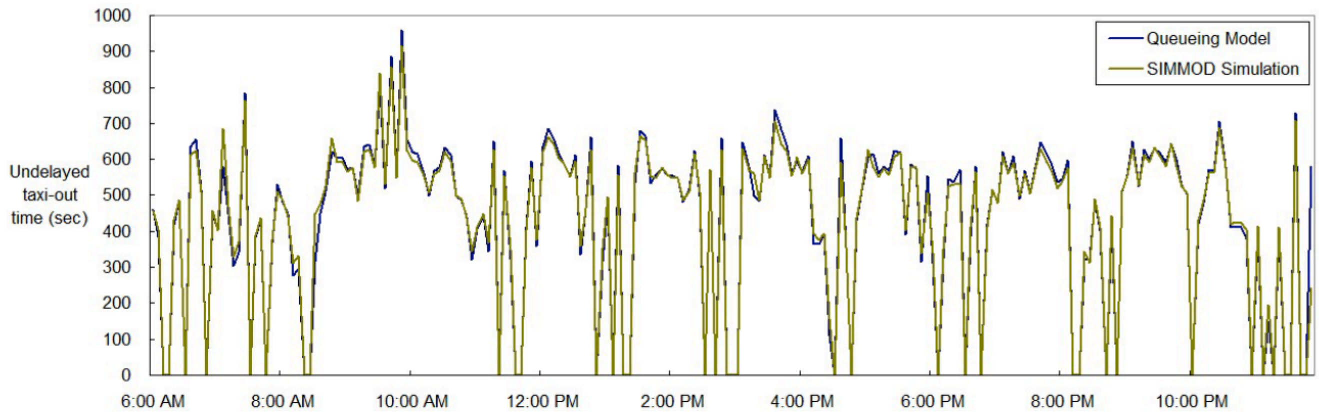


**Figure 4. Unimpeded Taxi-out Time Comparison between SIMMOD Simulation and Queueing Model**

### *Flight Schedules Used in Simulations*

One hour of data at DTW between 7:00PM and 8:00PM on August 1st, 2007, which is one of the busiest times on that day, is used as a baseline in the following SIMMOD simulations. Two different flight schedules are used in each experiment, the first corresponding to the originally scheduled pushback times, and the second corresponding to the optimized pushback times obtained by holding flights at their gates (gate-holding strategy). The optimized flight schedule is obtained by solving the aircraft taxi-scheduling problem to minimize the total taxi time, subject to the safety and operational constraints [22]. The pushback times are optimized so that their takeoff times are appropriately separated, and so that the ground delays and the sizes of departure queues are minimized. Arrivals are also simulated to create a realistic surface environment.

## Uncertainty Scenarios

Several parameters in the SIMMOD input data are varied using random seeds. SIMMOD can repeat the entire surface traffic movements with the given input and with randomly generated parameters as many times as needed. After iterating simulation runs, SIMMOD outputs statistics from the simulation results, such as movement start and end times for each flight, average travel times and delays on the ground and in the airspace, and fuel burn (if available).

### *Pushback Time Perturbation*

Taxiway optimization models generally assume that flights leave the gates exactly at the optimized pushback times. In reality, however, uncertainties in the pushback process make it very unlikely for an aircraft to meet its assigned pushback time. A flight may move out from the gate later than the scheduled pushback time due to late passengers, delayed loading of galley carts for cabin service, unexpected maintenance checks, waiting for clearance from the control tower, or communication with ground crews. Similarly, a flight may depart earlier if there are no delays or disruptions during pushback.

This uncertainty in pushback time can be modeled in SIMMOD by using randomized gate service times within a given range. For example, if flight A is scheduled to depart at 9:00AM and the mean gate service time is 30 minutes, then flight A will show up at 8:30AM in SIMMOD simulation in the absence of uncertainty. If we allow ±5min deviation from the mean value of gate occupancy times, the actual pushback time will be chosen as a random value between 8:55AM and 9:05AM. Each flight in the flight schedule has a different deviation independently drawn from the given distribution. The deviation from the deterministic flight schedule is assumed to range between 0 min (no uncertainty) and 5 min. In this case study, a truncated Gaussian distribution and a uniform distribution are considered for the pushback time uncertainty.

The random variables for gate occupancy times are applied to the 1-hr flight schedule described in the previous section. For each probability distribution, 100 different flight schedules are generated and simulated in SIMMOD for both the initial and optimized pushback schedules.

Table 2 summarizes the total ground delay per iteration in minutes categorized by runway (and averaged over 100 trials). For each pushback schedule, the deterministic case is used as a baseline. We see that the ground delay increases for both departure runways 21R and 22L, as the uncertainty of pushback times increases from deterministic to Gaussian, and then to a uniform distribution. By contrast, there is little effect on arrivals because the landing schedules remain deterministic. The simulations also demonstrate the benefits of the gate-holding policy. For the departure runway 22L, the optimized pushback schedule has a lower ground delay even with uniformly distributed pushback uncertainty compared to deterministic case with no gate-holds. This result suggests that the solutions recommended by deterministic surface traffic optimization provide benefits even in the presence of uncertainty.

**Table 2. Impact of Pushback Time Uncertainty on the Ground Delay**

| **Flight Schedule** | **Probability Distribution** | **Average Total Ground Delay/ Simulation Run (min)** | | | |
|---|---|---|---|---|---|
| | | **21R_Dep** | **22L_Dep** | **22R_Arr** | **27L_Arr** |
| Initial Pushback Time | Deterministic | 5 | 49 | 1 | 1 |
| | Gaussian | 8 | 54 | 1 | 0 |
| | Uniform | 9 | 56 | 1 | 0 |
| Optimized Pushback Time | Deterministic | 1 | 15 | 1 | 0 |
| | Gaussian | 8 | 32 | 1 | 0 |
| | Uniform | 9 | 36 | 1 | 0 |

This experiment can be extended to observe the effects of the deviation limit on the ground delay. The actual pushback time of a flight may sometimes be beyond the 5 min deviation from the schedule. So, the same simulations are implemented with various deviation limits from the deterministic pushback times, ranging from 0 to 15 minutes. In terms of flight operations, however, it is not allowed that a flight leaves the gate more than 5 minutes earlier than the schedule in the simulations. Using the same 1-hr flight schedule data, 100 different samples in which the pushback times of departures are randomly selected over the given range are generated and run in SIMMOD for each pushback time deviation limit.

Figure 5 presents the total simulated ground delay of departures as a function of the maximum pushback time deviation. For both departure runways, the ground delays for both the original and optimized pushback time schedules increase until the range of the pushback time perturbation becomes ±5 min from the given schedule. For the scheduled pushback time case, the delay for Runway 22L decreases gradually when the allowed deviation increases beyond 5 min. This reduction shows that the unintended pushback delays may act as an implicit gate-holding policy when the departure traffic demand is very high, by keeping aircraft at their gates until the surface congestion has decreased.

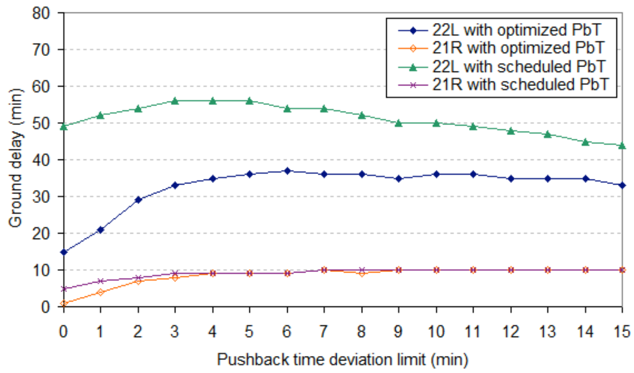


**Figure 5. Total Ground Delay with Pushback Time Perturbation**

### *Runway Exit Time Perturbation*

Arrivals also have uncertainty associated with their runway exit times, that is, the times when they enter the taxiway system. This uncertainty can be modeled by varying the landing roll distances in SIMMOD. The landing roll distance is affected by many factors, such as aircraft weight, approach speed, braking performance, headwind, runway surface condition, slope, and human factors. In this study, the deviation range from the normal landing roll distance used in SIMMOD is set to ±500 ft. It is also assumed that arrivals use the same runway exit so as restrict the uncertainty to the runway exit time alone.

For the same flight data as the previous case study, 100 trials were implemented by using random seeds in SIMMOD. The Monte Carlo simulations showed no effect on the ground delay. The perturbation in roll distance impacted just the gate-in time of each arrival. This result is reasonable since the inter-arrival times give consecutive flights sufficient spacing on the taxiway.

### *Taxi Speed Perturbation*

The objective of the case studies described in this section is to investigate the impact of flights moving at differing taxi speeds on the ground delay. In the previous simulations, it was assumed that all flights taxiing on the ground move at the same taxi speed, which is the average value of various taxi speeds observed at the airport. With this assumption, the trailing flight on a taxiway keeps a constant separation distance from the leading flight on the same route. In practice, however, taxi speeds may differ from flight to flight due to factors such as aircraft type, pilot behavior, operational procedures, taxiway length, etc. [23]. We therefore simulate differing taxi speeds, and scrutinize the impact of taxi speed perturbation on ground delays.

**Case study 1 - Taxi speed perturbation on taxiways**

First, it is assumed that the pushback times for departures and the runway exit times for arrivals are known and deterministic. Each flight is assumed to have a different taxi speed within a given range on the taxiway area, which it maintains along the entire taxi route. SIMMOD cannot vary the speed of a flight while it is taxiing. The upper and lower bounds of the taxi speed range would be determined by the ground congestion and operational rules at the airport. All flights are assumed to maintain a speed of 7 knots in the ramp areas. We assume that there are no significant differences in taxi speeds based on aircraft type or between arrivals and departures.

The same 1-hr flight schedule data at DTW as the previous uncertainty studies is used. Values within the given taxi speed range are randomly generated using a uniform distribution, and assigned to the flights in the schedule. The mean value of the taxi speed is set to 18 knots, which is consistent with the parameters used in the optimization model for aircraft taxiway scheduling.

For the Monte Carlo simulation, 100 trials with randomly generated taxi speeds are run by SIMMOD. The data sets contain the same flight schedules, pushback times and landing times, but different taxi speeds are assigned to the same flight in each trial. To investigate how the uncertainty in taxi speed affects the ground delay, six different taxi speed ranges are studied. Also, for comparison, the simulations are conducted with the original schedule and the optimized pushback time schedule.

Tables 3 and 4 show the total ground delays (averaged over the 100 trials) from the SIMMOD simulations of the original and optimized flight schedules. The total ground delay includes holding for runway crossings, intersection holds to avoid conflicts, wait times in the departure queue, and holds for maintaining separation on the taxiway due to a slower flight ahead.

**Table 3. Total Ground Delay (in min) for the Original Flight Schedule with Taxi Speed Perturbation**

| **Taxi Speed Deviation** | **0** | **1** | **2** | **3** | **4** | **4.8** |
|---|---|---|---|---|---|---|
| **Taxi Speed Range (knots)** | [18, 18] | [17, 19] | [16, 20] | [15, 21] | [14, 22] | [13.2, 22.8] |
| **Departure Runway 22L** | 49.00 | 51.65 | 53.03 | 55.17 | 60.94 | 66.20 |
| **Departure Runway 21R** | 5.00 | 6.08 | 7.78 | 9.72 | 12.41 | 14.77 |
| **Arrival Runway 22R** | 1.00 | 0.94 | 1.78 | 2.45 | 4.07 | 5.11 |
| **Arrival Runway 27L** | 0.00 | 0.57 | 1.04 | 2.05 | 2.75 | 2.57 |

**Table 4. Total Ground Delay (in min) for the Optimized Flight Schedule with Taxi Speed Perturbation**

| **Taxi Speed Deviation** | **0** | **1** | **2** | **3** | **4** | **4.8** |
|---|---|---|---|---|---|---|
| **Taxi Speed Range (knots)** | [18, 18] | [17, 19] | [16, 20] | [15, 21] | [14, 22] | [13.2, 22.8] |
| **Departure Runway 22L** | 20.00 | 18.04 | 18.79 | 24.63 | 32.84 | 40.39 |
| **Departure Runway 21R** | 1.00 | 3.60 | 6.33 | 9.23 | 12.22 | 14.47 |
| **Arrival Runway 22R** | 0.00 | 1.38 | 2.08 | 2.97 | 4.25 | 5.01 |
| **Arrival Runway 27L** | 0.00 | 0.61 | 1.03 | 2.01 | 2.40 | 2.49 |

Figure 6 graphically shows the total ground delays (averaged over 100 simulations) from Table 3 and 4. The ground delay for departures increases as the taxi speed range increases. This tendency is to be expected because the taxi speeds of flights are constrained by slower flights. For instance, if a leading flight is slower than a group of flights behind it along the same taxi route, the trailing flights cannot taxi faster than the leading one, resulting in increased taxi times and wait times in the departure queue. In rare cases, ground delays can be decreased with increased taxi speed perturbation because the different taxi speeds may increase separation on taxiway and runway. However, the total ground delay generally increases as the taxi speed range increases.

By contrast, there is little impact on the ground delay of arrivals since the total delay for the approximately 30 arrivals from each runway is less than 5 min for any of the taxi speed ranges. This result is due to the fact that arrivals are already separated enough when exiting the runway, resulting in minimal interactions with the following aircraft. Taxi routes for arrivals are almost independent on the paths for departures, except in the ramp area, further minimizing interactions between them.

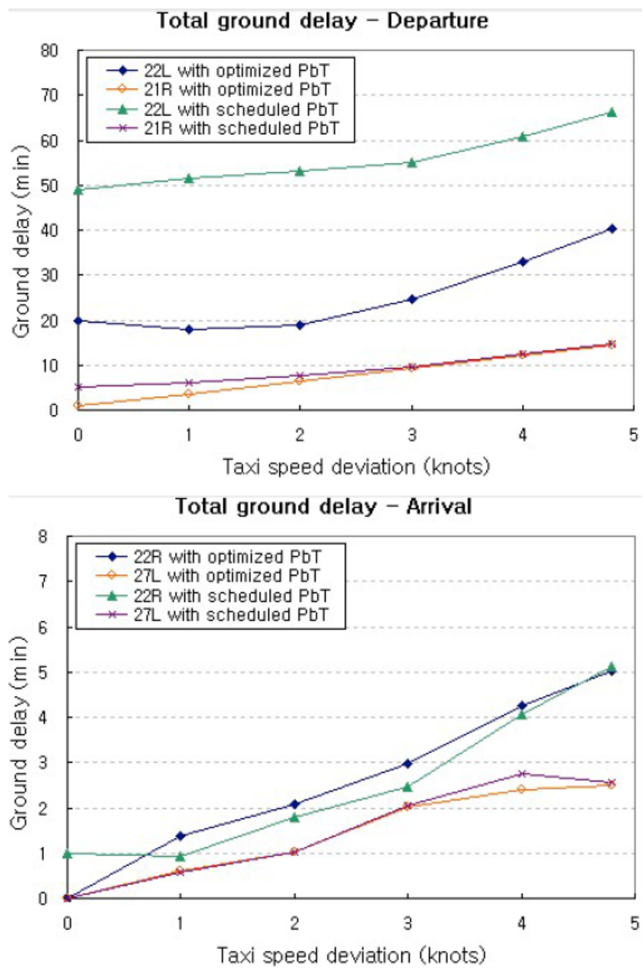


**Figure 6. Total Ground Delay with Taxi Speed Perturbation on Taxiway**

In the simulation results, the original and optimized pushback time schedules are also compared. For the more congested runway (Runway 22L), the ground delay of the optimized pushback time schedule is always much less than the delay of the original schedule. The ground delay values for the two schedules are similar for the less congested runway (Runway 21R), and they become more similar as the taxi speed deviation increases. The *additional* ground delay compared to the deterministic case is greater for the optimized schedule case as the taxi speed deviation increases, possibly because the optimized flight schedule is more sensitive to taxi speed uncertainty.

### Case study 2 - Taxi speed perturbation on taxiway and ramp areas

In the previous case study, different taxi speeds were applied to the taxiway areas only. This uncertainty can be extended to the ramp area where aircraft move from/to gates around the terminals at slower speed. When the flights move both on the ramp and taxiway areas at differing speeds, ground delay is expected to increase because of increased interactions, especially in the ramp area.

As in the previous case, taxi speed values perturbed around the average taxi speed are assigned to flights. The same deviation is applied to the taxi speed values on both ramp area and taxiways. For example, if the random deviation of a flight is +1.5 knots, the assigned speed will be 19.5 knots on the taxiway and 8.5 knots in the ramp area.

Figure 7 shows the total ground delay for each runway. As expected, the absolute values of the ground delay are significantly increased for all cases, compared to Figure 6. As in the previous case study, the delay increases as the taxi speed range increases. In contrast to the previous results, arrivals also experience increased ground delay due to taxi speed perturbation. This fact is due to arrivals sharing the ramp area with departures. It is worth noting that most arrival ground delays in the SIMMOD simulations occur in the ramp area. We also note that the optimized pushback time schedule shows much less delay for Runway 22L and a slightly worse delay for Runway 27L compared to the original schedule, while the other values are almost the same.

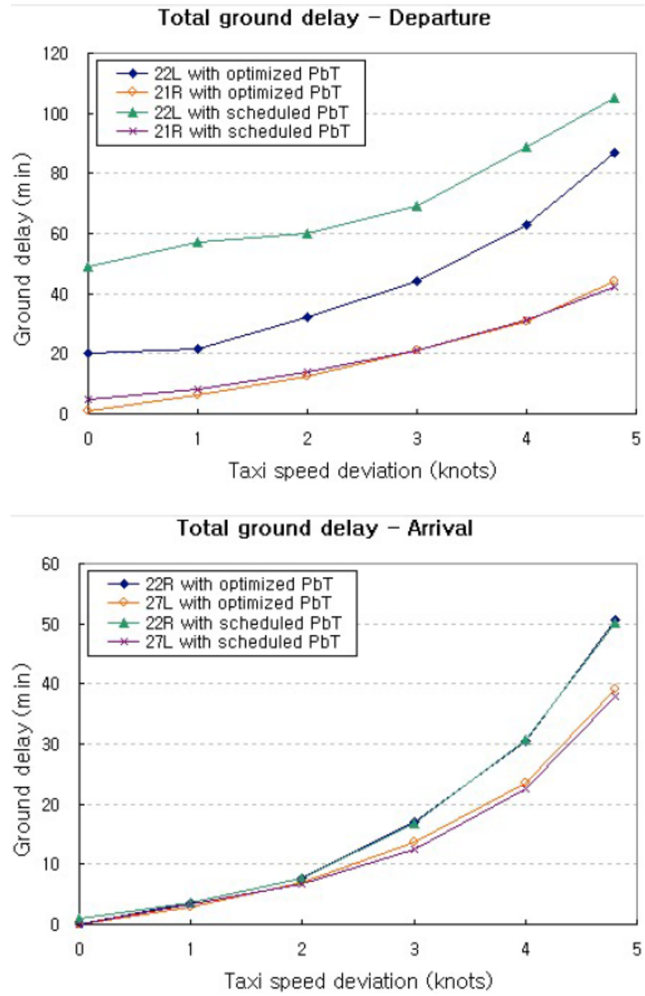


**Figure 7. Total Ground Delay with Taxi Speed Perturbation on Taxiway and Ramp Areas**

### Case study 3 - Taxi speed perturbation on taxiway and ramp areas, with faster arrivals

The prior case studies assumed that there was no difference between arrivals and departures in terms of taxi speeds. However, arrivals tend to taxi faster in practice. Analysis of surface surveillance data at DFW has shown that arrivals are about 2 knots faster than departures while taxiing [23]. While the average taxi speed was assumed to be 18 knots in the previous case studies, the mean values of taxi speeds in this case study are assumed to be 17 knots for departures and 19 knots for arrivals on the taxiway. On the ramp area, however, it is assumed that both departures and arrivals have the same average of 7 knots.

The resultant total ground delays for this case study are shown in Figure 8. The total ground delay variation with taxi speed deviation in Figure 8 is almost same as in Figure 7, suggesting that ground delay is not affected by the absolute values of the average taxi speed, but only by the deviation range. The average taxi speed value affects the unimpeded taxi time alone.

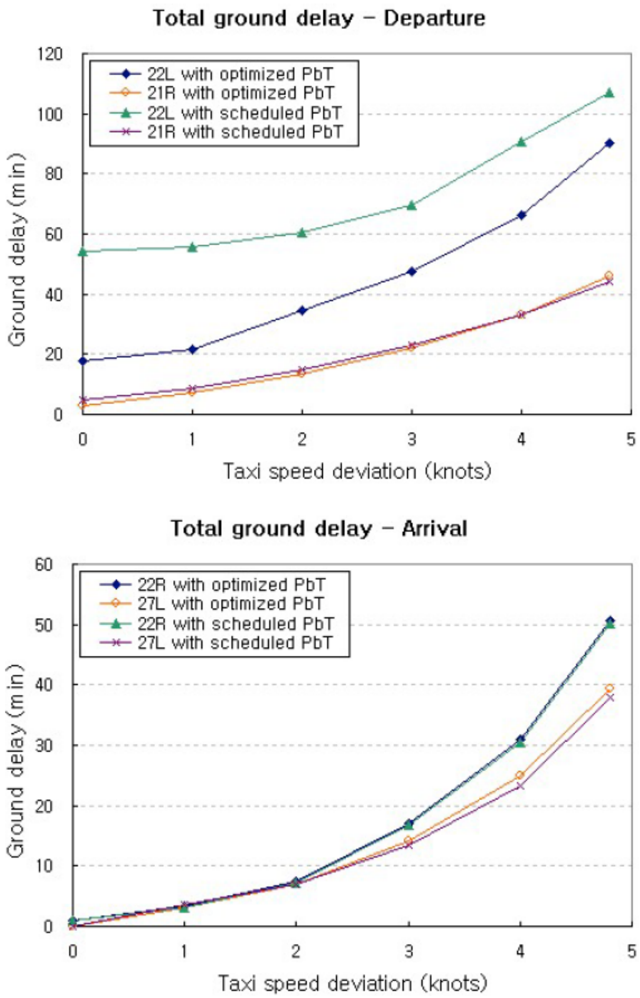


**Figure 8. Total Ground Delay with Taxi Speed Perturbation on Taxiway and Ramp Areas with Faster Arrival Taxi Speeds**

### *Inter-Departure Time Perturbation*

The takeoff separation times between consecutive departures differ in real operations, even when the weight classes are the same. The inter-departure separation time variation is modeled in SIMMOD using a random variable for the in-trail separation multiplier. This factor multiplies the minimum separation time to yield the separation time in the simulation. In this analysis, various separation times between takeoffs are randomly generated in SIMMOD within the given range, while the minimum separation requirements are maintained. The upper limit of the in-trail separation multiplier applied in this experiment ranges from 1.0 (tight separation) to 1.5 (conservative operation). For each case, 100 simulation runs are performed.

Figure 9 shows the total simulated ground delay along with the upper limit of the separation time multiplier, depending on the runway and on the flight schedule. As expected, the ground delay linearly increases as the range of separation times widens. The increased delay on the ground comes from the increased wait time in the departure queue because the following flight needs to wait longer before takeoff. Furthermore, the waiting time is propagated when the departure queue is full. For Runway 22L in the graph, the ground delay for the optimized pushback time case reaches 49 minutes when the multiplier limit is 1.4, implying that conservative runway operations can cancel out the benefits from taxiway schedule optimization. It is also evident that the separation time uncertainty can decrease runway throughput.

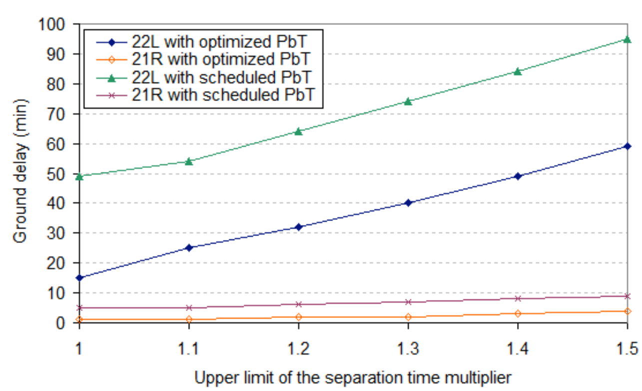


**Figure 9. Total Ground Delay with Separation Time Perturbation**

## Conclusions

In this paper, significant uncertainty factors in airport operations were identified, and stochastic simulations using SIMMOD were developed for evaluating the impacts of the uncertainty on airport performance. The simulation model was validated with an actual flight schedule at DTW. Monte Carlo simulations for various uncertainty scenarios were then conducted for various flight schedules at DTW.

Simulation results showed that the ground delay increased as the uncertainty in pushback times grew. By contrast, uncertain runway exit times for arrivals did not significantly impact airport performance, apart from gate arrival times. It was also shown that perturbations in taxiway speeds resulted in significant increases in ground delay for departures. By contrast, the taxi-in times of arrivals increased only when there were taxi speed variations in the ramp area, where arrivals interact with departures; however, the ground delay did not depend on the absolute value of the average taxi speed. Uncertainty in inter-departure separation times increased wait times in the departure queue, while reducing runway throughput.

The case studies presented in this paper also compared simulations of originally scheduled and optimized pushback times and showed that the surface traffic optimization based on a deterministic model can still provide benefits in the presence of uncertainties.

Future work will involve the evaluation of other sources of uncertainty and performance metrics in a similar manner using SIMMOD. Since these uncertainties usually occur together in the real world, the combined impacts of different sources of uncertainty will need to be studied as well.

## References


[1] Brinton, Chris, Steve Atkins, May 2009, A Probabilistic Modeling Foundation for Airport Surface Decision Support Tools, Arlington, VA, Integrated Communication, Navigation and Surveillance Conference.

[2] Cobb, Paul, Karlin Roth, Ari Stassart, George Couluris, Doug Sweet, and George Hunter, August 2004, A Modeling Architecture for Capturing CNS Uncertainty and Prediction Errors in the NAS, Providence, RI, AIAA Modeling and Simulation Technologies Conference and Exhibit.

[3] Koeners, Joris, Richard Rademaker, August 2011, Creating a Simulation Environment to Analyze Benefits of Real-time Taxi Flow Optimization Using Actual Data, Portland, OR, AIAA Modeling and Simulation Technologies Conference and Exhibit.

[4] Atkins, Stephen, Christopher Brinton, and Yoon Jung, September 2008, Implications of Variability in Airport Surface Operations on 4-D Trajectory Planning, Anchorage, AK, AIAA Aviation Technology, Integration and Operations (ATIO) Conference.

[5] Brinton, Christopher R., Lara S. Cook, and Stephen C. Atkins, 2007, Collaborative Airport Surface Metering for Efficiency and Environmental Benefits, Dulles, VA, Proceedings of the Integrated Communication, Navigation and Surveillance Conference.

[6] Brinton, Christopher R., Stephen C. Atkins, and Abraham Hall, 2007, Analysis of Taxi Conformance Monitoring Algorithms and Performance, Dulles, VA, Proceedings of the Integrated Communication, Navigation and Surveillance Conference.

[7] Simaiakis, Ioannis, Hamsa Balakrishnan, August 2009, Queuing Models of Airport Departure Processes for Emissions Reduction, Chicago, IL, AIAA Guidance, Navigation, and Control Conference.

[8] Jordan, Richard, Mariya A. Ishutkina, and Tom G. Reynolds, October 2010, A Statistical Learning Approach to the Modeling of Aircraft Taxi Time, Salt Lake City, UT, 29th Digital Avionics Systems Conference.

[9] Atkin, Jason A. D., Edmund K. Burke, and Stefan Ravizza, June 2010, The Airport Ground Movement Problem: Past and Current Research and Future Directions, Budapest, Hungary, Proceedings of the 4th International Conference on Research in Air Transportation (ICRAT).

[10] Gotteland, Jean-Baptiste, Nicolas Durand, Jean-Marc Alliot, and Erwan Page, 2001, Aircraft Ground Traffic Optimization, Santa Fe, NM, Proceedings of the 4th USA/Europe Air Traffic Management R&D Seminar.

[11] de Neufville, Richard, Amedeo Odoni, 2003, Airport Systems: Planning, Design and Management, McGraw-Hill.

[12] Odoni, Amedeo R., Jean-Marc Rousseau, and Nigel H.M. Wilson, 1994, Models in Urban and Air Transportation, Handbooks in Operations Research and Management Science, Elsevier Science B. V., Chapter 5.

[13] ATAC Corporation, 1995, SIMMOD Reference Manual, http://www.atac.com/.

[14] AirportTools, 2005, Basic SIMMOD Study Creation Tutorial, http://www.airporttools.com/.

[15] Delcaire, Bertrand, Eric Feron, December 1997, Development of an On-site Ground Operations Model for Logan International Airport, Cambridge, MA, Final Report, FAA Air Transportation Center of Excellence in Operations Research, MIT.

[16] Martel, Nathalie, January 2000, SIMMOD-Based Simulation Montreal Dorval (YUL) Case Study. TRB Workshop on Airport-Airspace Simulations for Capacity Evaluation.

[17] Trani, Antonio A., September 2000, Runway Occupancy Time Estimation and SIMMOD, Chicago, IL, North American SIMMOD User's Group Meeting.

[18] Kleinman, Nathan L., Stacy D. Hill, and Victor A. Ilenda, June 1997, SPSA/SIMMOD Optimization of Air Traffic Delay Cost, Albuquerque, NM, Proceedings of the American Control Conference.

[19] Gao, Wei, Xiaohao Xu, Lin Diao, and Hongjun Ding, October 2008, SIMMOD Based Simulation Optimization of Flight Delay Cost for Multi-airport System, Hunan, China, Intelligent Computation Technology and Automation (ICICTA).

[20] Simaiakis, Ioannis, Hamsa Balakrishnan, December 2010, Impact of Congestion on Taxi Times, Fuel Burn and Emissions at Major Airports, Transportation Research Record: Journal of the Transportation Research Board, No. 2184, pp. 22-30.

[21] Lee, Hanbong, Ioannis Simaiakis, and Hamsa Balakrishnan, October 2010, A Comparison of Aircraft Trajectory-based and Aggregate Queue-based Control of Airport Taxi Processes, Salt Lake City, UT, 29th Digital Avionics Systems Conference.

[22] Lee, Hanbong, Hamsa Balakrishnan, October 2012, A Comparison of Two Optimization Approaches for Airport Taxiway and Runway Scheduling, Williamsburg, VA, 31st Digital Avionics Systems Conference, To be submitted.

[23] Gong, Chester, September 2009, Kinematic Airport Surface Trajectory Model Development, Hilton Head, SC, AIAA Aviation Technology, Integration and Operations (ATIO) Conference.

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