AIRPORT CONTROL THROUGH INTELLIGENT GATE ASSIGNMENT

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AIRPORT CONTROL THROUGH INTELLIGENT GATE ASSIGNMENT

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SUMMARY

This dissertation aims at improving the efficiency, robustness, and flexibility of airport operations through intelligent gate assignment. Because airport resources are insufficient to satisfy growing traffic demands, it is required to manage airport operations with the current resources. Among various stages in airport operations, ramp operations influence both air-side and land-side operations as well as both arrival and departure operations. Therefore, this dissertation focuses on controlling ramp operations through gate assignment. Traditional research on gate assignment focuses on the accommodation of passengers' demands such as walking time of passengers, and the robustness of gate assignment. In spite of its importance on the ramp operations, there is a lack of research to account ramp congestion when gates are assigned. Therefore, this dissertation proposes a new perspective on the gate assignment that accounts for ramp congestion. For that purpose, it is necessary to better understand ramp operations focusing aircraft movements, and a ramp operations model based on observations at Hartsfield-Jackson Atlanta International Airport is presented to understand the characteristics of aircraft movement on the ramp. The proposed gate assignment problem minimizes total passenger-time spent on ramp areas so that the traffic flow on the ramp becomes more efficient. In order to solve the gate assignment problem, Tabu search algorithm is used because it is known to efficiently deal with the gate assignment problem. Two types of neighborhood search moves are implemented in the Tabu search algorithm: Insert move switches an aircraft's gate assignment from one gate to another, and interval exchange move swaps two groups' gate assignments. In addition, it is required to consider various aspects (transit time, ramp congestion, and robustness) of gate assignment altogether. So, this dissertation is conducted

to satisfy the needs of passengers, aircraft, and operations from the perspectives of passengers. Using actual passenger data at a major hub airport, the proposed gate assignment is assessed by means of passengers' transit time, passengers' time spent on the ramp, and passengers' waiting time for a gate. Results show that the proposed gate assignment outperforms the current gate assignment at the hub airport in every metric. This dissertation also analyzes the impact of gate assignment on departure metering. When an airport is congested, departure metering controls the number of pushbacks in order to reduce airport congestion. Then, some of departing flights are held at gates, so it increases the chance of gate conflict, which occurs when an arrival requests a gate that is still occupied by a departure. The gate conflict disturbs ramp operations and reduces the efficiency of departure metering as well as ramp operations. In order to analyze the impact of gate assignment on departure metering, this dissertation simulates departure processes at two airports. Results show that the proposed robust gate assignment reduces the occurrence of gate conflicts under departure metering and helps air navigation service provider to utilize gate-holding times to an extent.

CHAPTER I

INTRODUCTION

1.1   Future Air Traffic Demand and Motivation

The Federal Aviation Administration (FAA) forecasts that one billion passengers will fly on U.S. commercial air carriers in 2021 according to its 2011 report [29]. In particular, the air traffic demand for U.S. commercial air carriers will grow at an average rate of 3.7 percent per year from 2011 to 2016 and 2.5 percent per year from 2016 to 2021. The expected growth of air traffic demand is shown in Figure 1. In order to meet the increasing air traffic demand while satisfying safety requirements and reducing environmental impact, the FAA initiated the Next Generation Air Transportation System (NextGen), defined as follows: "NextGen is an umbrella term for the ongoing transformation of the National Airspace System (NAS)" [31]. NextGen helps airports to be prepared to meet the anticipated growth of future air traffic in a safe, efficient, and sustainable way [32]. For instance, Collaborative Departure Queue Management (CDQM) helps reduce congestion and emission on airport surface. A simple version of CDQM, which is N-Control, was demonstrated at Boston Logan International Airport [63]. Along with the objectives of NextGen for airports, this study aims at increasing efficiency and flexibility, and improving collaborative air traffic management in airport operations.
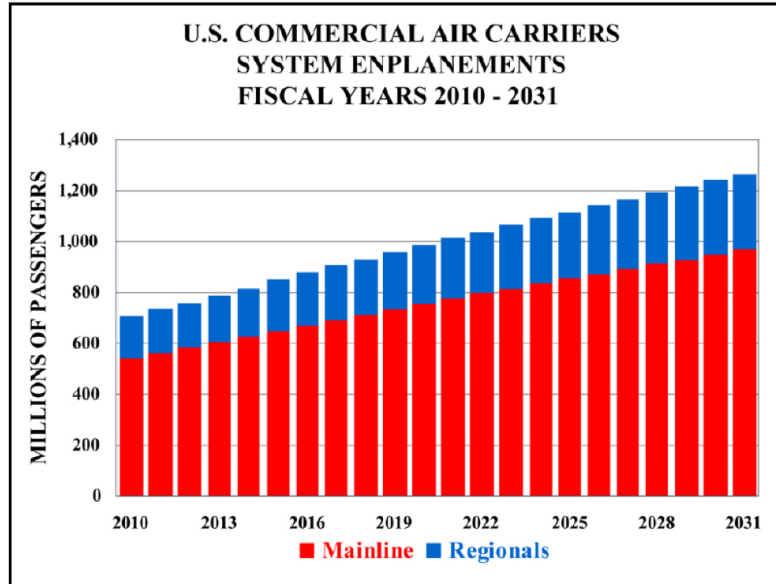
Figure 1: The 2011 FAA Forecast on the Number of Passengers [29].

An airport is one of the bottlenecks of the air transportation system [19]. In addition, it is a scarce and valuable resource because, although more airport resources are made available, they are insufficient for the demands of future air traffic. As indicated by the 2011 FAA forecast, passenger air traffic is expected to grow, but at the same time airport capacity is not likely to satisfy the increasing demands of air traffic due to limited resources. Construction of new runways or runway expansion will increase the capacity of the airport, but it costs a huge amount of money. For instance, Fort Lauderdale-Hollywood International Airport is expanding a runway, and the estimated cost for the expansion is 791 million dollars [58]. However, such an expansion or construction project is not always possible. For example, New York's La Guardia Airport suffers from severe delays due to high travel demand into and out of New York City, but there is no space even to expand a runway. So, it is sometimes necessary to manage congestion at an airport given the current airport resources.

This study categorizes the airport operations into air-side and land-side operations. The air-side operations include airport surface operations such as take-off, taxi, pushback, etc., and the land-side operations are related to passengers. In the

air-side airport operations, many stakeholders are involved, such as the FAA, airport authorities, and airlines. For example, runways and taxiways are controlled by the airport traffic control tower, but ramp areas in many large airports are managed by separate ramp towers where airlines take part. For instance, there are three ramp towers at Hartsfield-Jackson Atlanta International Airport, and one of them is operated by Delta Air Lines and the others are controlled by TBI Airport Management. Therefore, there is potential conflict of interest between airport authority and airlines, and collaborative ramp management is required for safe and efficient airport ramp operations. Figure 2 illustrates airport operations. This study focuses on the optimization of ramp operations and the accommodation of passengers. As shown in Figure 2, a ramp area is the place where arrival operations turn into departure operations and air-side operations interact with land-side operations. Therefore, controlling ramp operations leverages control over the whole airport.
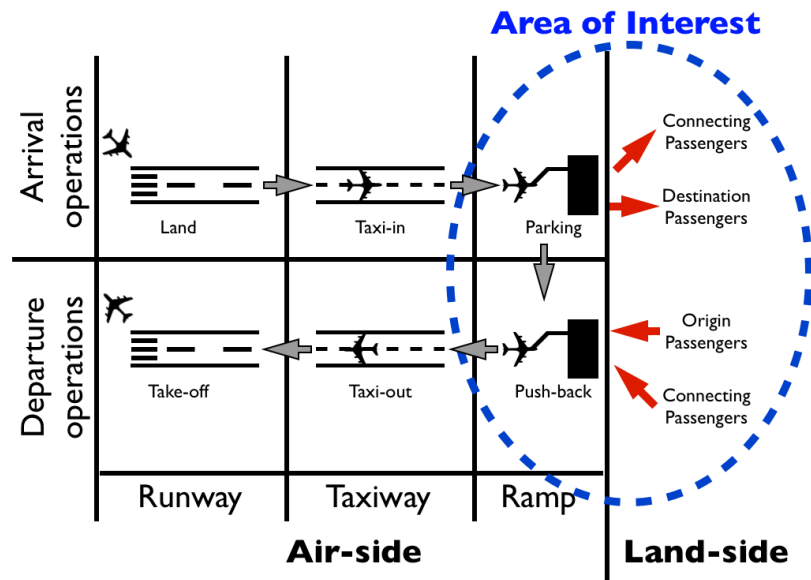
Figure 2: A Synopsis of Airport Operations. The area of interest of this dissertation is optimal gate assignment, accounting for aircraft and passenger performance metrics.

1.2 Background on the Gate Assignment Problem and Literature Review

The ramp area is a complex portion of the airport, with congestion and interactions between aircraft often limiting the efficient flows of arriving and departing aircraft. Among the most important airport resources, gates allow passengers to board and disembark from aircraft. Once a gate is assigned to an aircraft for a given time slot, it cannot be reassigned to another aircraft during that period. Therefore, the appropriate utilization of gate resources can be beneficial in reducing passenger delays and relieving ramp congestion.

1.2.1 Traditional Gate Assignment Problem

The Gate Assignment Problem (GAP) is a research field that studies efficient utilization of airport gates. Traditional approaches to the GAP are mainly concerned with minimizing the walking distances of passengers within the airport. Gate assignments can be achieved by optimization methods, and a number of researchers have developed various optimization models. For example, Mangoubi and Mathaisel assumed that the expected walking distance of connecting passengers are distributed uniformly, and they formulated the GAP to minimize passenger walking distances from/to the main terminal as a quadratic assignment problem [52]. Haghani and Chen accounted for connecting passengers as well as origin and destination (O&D) passengers [38]. They assumed that all passengers are connecting passengers including those who do not actually transfer flights at the airport and suggested a virtual gate to represent the entrance/exit of the airport. Due to the complex nature of the GAP, they proposed a heuristic algorithm to obtain a solution efficiently. Ding, et al. focused on minimizing the number of flights that are assigned to a parking spot on the ramp at over-constrained airports [25, 26]. They minimized the number of un-gated flights and then optimized passenger walking distances. More details about recent

developments regarding the GAP are available in the survey conducted by Dorndorf et al.[27]

As mentioned above, the GAP can be seen as a quadratic assignment problem of the kind initially considered by Koopmans and Beckmann to solve the problem of allocation of economic resources [48]. Their problem is relatively simple because the quadratic cost coefficients are decoupled to the transportation cost between two locations and the flow cost between two plants. Lawler presented a general quadratic assignment problem and an equivalent linear problem [50]. He also discussed various applications of the quadratic assignment problem. Pardalos et al. [60] and Burkard et al. [18] surveyed the state of the art on the quadratic assignment problem, several linearization techniques and various solution methods, including exact methods and heuristic algorithms.

1.2.2 Robust Gate Assignment

Severe weather conditions, unanticipated system errors, or incidents at an airport cause flight delays, which are propagated to other airports because the entire air traffic network is connected. From time to time, flight delays accumulate because of the network effect. The network effect comes from airports, or more specifically gates. A single aircraft is assigned to a series of flight legs on a daily basis; a flight leg ends and the next flight leg begins at an airport gate. Therefore, if a flight leg is delayed for some reason, the following flight leg (tail-connected flight) is likely to be delayed and the gate occupied by the aircraft will be released later than the scheduled time. Since the gate is assigned to other aircraft subsequently, a delay of an aircraft may cause serial delays of the following aircraft that are assigned to the same gate. Such a propagation of delay results from the fact that numerous aircraft use airport gates and their gate schedules are dense. For instance, one aircraft is assigned to flight number DL0812, which flies from West Palm Beach, FL to Atlanta, GA. After

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the flight, the same aircraft is given to another flight number DL1490, which departs from Atlanta, GA to Minneapolis, MN [14, 33]. If the flight incoming to Atlanta, DL0812, arrives late, then the tail flight, DL1490, is also going to depart late.

As discussed above, delays can be propagated through airport gates and the propagated delays are harmful to the efficiency of the air traffic network. A proper gate assignment can help reduce the propagation of delays by absorbing some portion of delays in the time gap between gate schedules. Therefore, robustness becomes another important issue of the GAP because flight delays are uncertain and hard to estimate precisely. Robust gate assignment is thought to be the type of assignment that is insensitive to variations in flight schedules [9, 10] and that minimizes the number of gate-reassigned aircraft [51]. In order to achieve robust gate assignment, many researchers have attempted various methods. For example, buffer times are used to absorb stochastic flight delays to some extent [39, 9, 69]. Buffer time is the minimally required amount of gate separation, which is the term for the time gap between two consecutive gate schedules. An example of a series of gate schedules and corresponding gate separations are shown in Figure 3.
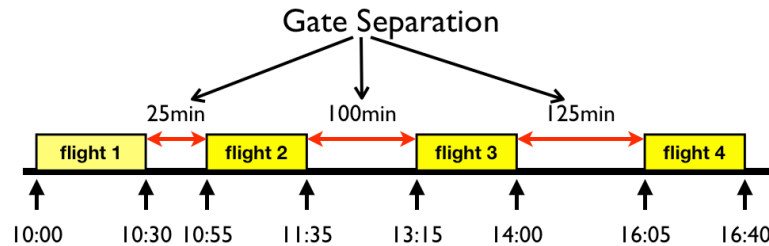
Figure 3: A Series of Gate Schedules and Corresponding Gate Separations.

If an aircraft is severely delayed and departs later than the scheduled time, the aircraft occupies the assigned gate longer, and the next aircraft that is assigned to the gate may not access the gate on time. Then, the gate assignment is disturbed, and such a situation is called gate conflict. If the previous aircraft is not delayed severely or the amount of departure delay is less than the gate separation between the delayed

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aircraft and the following aircraft, the gate assignment is not disturbed, and the next aircraft can access the assigned gate without any additional delay. This shows that gate separations influence the probability of gate conflict and the punctuality of ramp operations as a result. However, if buffer time is too large, the utilization of gates is reduced. To address this issue, there is some research on designing buffer time. Yan et al. developed a simulation framework to analyze stochastic delays and designed buffer times that vary with traffic densities at an airport [70]. They evaluated the trade-off between maximizing gate utilization and maximizing the robustness of gate assignments. Long buffer time makes gate assignments robust against disturbances such as stochastic delays, but is unfavorable for efficient utilization of resources. On the other hand, short buffer time is advantageous for increasing gate usage, but gate assignments become sensitive to small changes in flight schedules.

Bolat studied maximizing idle times of gates (gate separations) [10]. Since the sum of gate occupancy times is constant, he tried to distribute gate separations evenly among aircraft. Lim and Wang defined gate conflict as occurring when two aircraft are assigned to the same gate and two durations of gate occupancy overlap [51]. They assumed that the gate separation determines the probability of gate conflict. They selected several candidate functions to estimate the probability of gate conflict and determined that an exponential function provides the most robust assignment compared to an inverse function, a linear function, and a sublinear function. However, their candidate functions were not based on an analysis of delays. Yan and Tang considered the interrelationship between gate assignment and stochastic flight delays [71]. They argued that real-time gate reassignments need to be accounted when gates are assigned. Although buffer time can absorb a minor modification of flight schedules, gate reassignment is occasionally required if a huge delay occurs, gates suddenly become out of order and so forth. Gu and Chung developed a genetic algorithm to reassign gates [36].

1.3 Gate Delay Analysis

Most uncertainties of ramp operations come from stochastic flight delays. Mueller and Chatterji analyzed characteristics of departure and arrival delays [55]. They selected ten major U.S. airports that experience significant delays and developed models that describe the stochastic nature of delays. They used Normal and Poisson distributions to predict departure, en route, and arrival delays. Tu et al. implemented a genetic algorithm to develop a model that captures seasonal and daily trends in departure delays [65]. Indeed, there are significant differences between seasons; for example, in winter, there are many cancellations and severe delays due to icy weather. They also showed that departure delays gradually stack up during the day and decrease at night. Xu et al. studied delay propagations in the National Airspace System (NAS) [68]. They categorized propagating patterns in turn around processes at Chicago O'Hare International Airport and showed how a delay at an origin airport can propagate to a destination airport. Bruinsma et al. investigated departure and arrival delays in European public transportation systems [13]. They took Gamma, Log-normal, and Weibull distributions as candidate models that describe delays. Although there are many studies on the development of a model that estimates delays, no specific model or any probability distribution is known to completely describe characteristics of delays.

A gate assignment is disturbed when two consecutive gate schedules overlap, that is, when an aircraft departs too late and/or the next aircraft arrives too early. For instance, suppose that two aircraft are assigned to a gate and their gate schedules are from 1:00PM to 2:00PM and from 2:30PM to 3:30PM. If the departure of the first aircraft is delayed until 2:20PM and the next aircraft arrives on time, this gate assignment is not disturbed. However, if the first aircraft is delayed 20 minutes more, then the gate is occupied when the next aircraft arrives. In this case, the duration of the gate conflict is 10 minutes. Longer duration means that the gate assignment

is more disturbed and less robust, and the following aircraft will be delayed. Thus, in this study, the robustness of gate assignments is measured as the duration of gate conflict. Because delays are uncertain, the expected value of the duration is used to evaluate the robustness of gate assignments.

Therefore, the analysis of gate delays is important to achieve robust gate assignment. The FAA has various databases of flight operations, including the Aviation System Performance Metrics (ASPM), which contains airport data and individual flight data. The airport data give capacities and throughput of airports for every 15 minutes, and the individual flight data provide scheduled and actual gate departure and arrival times and so forth. Also, the Bureau of Transportation Statistics (BTS) provides detailed statistics including scheduled departure/arrival times, actual departure/arrival times, delays, and other information. In order to analyze gate delays, this study uses both ASPM data and airline on-time statistics provided by BTS [14].

1.3.1 Gate Delay Model

As an example, gate delays of Northwest Airlines (NWA) at Detroit Metropolitan Wayne County Airport (DTW) in March 2006 are analyzed using airline on-time statistics provided by BTS [14]. During that period, there were 7923 departures and 7923 arrivals. The minimum and maximum of departure delays are -15 minutes (15 minutes earlier than schedule) and 380 minutes, and those of arrival delays are -48 minutes and 1245 minutes. The average and median of departure delays are 8.07 minutes and -1 minute, and those of arrival delays are 2.61 minutes and -4 minutes. The standard deviations of departure and arrival delays are 24.45 minutes and 39.83 minutes, respectively. The statistical characteristics tell that the distributions of departure and arrival delays shift to the left and arrival delays are distributed more sparsely than departure delays. Distributions of departure and arrival delays are shown in Figure 4 and Figure 5.
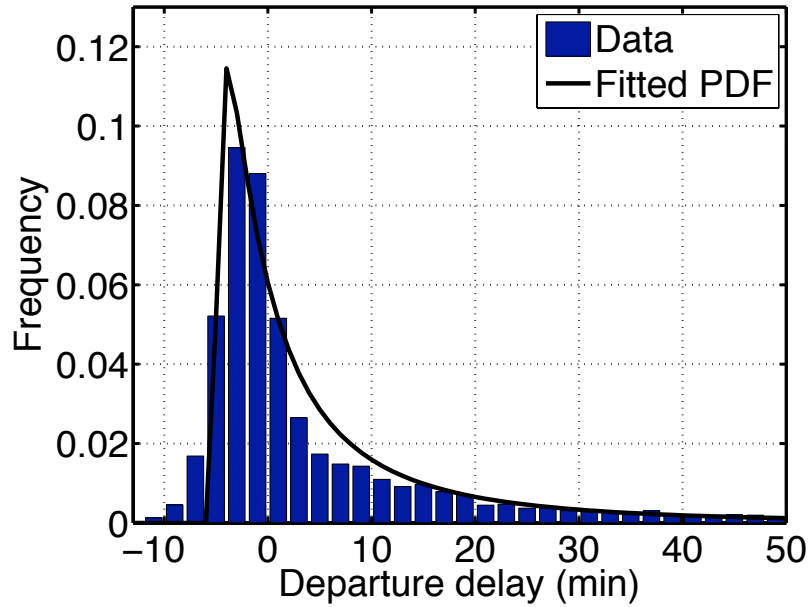
Figure 4: Departure Delay Distribution of NWA at DTW in March 2006 and the Fitted PDF.
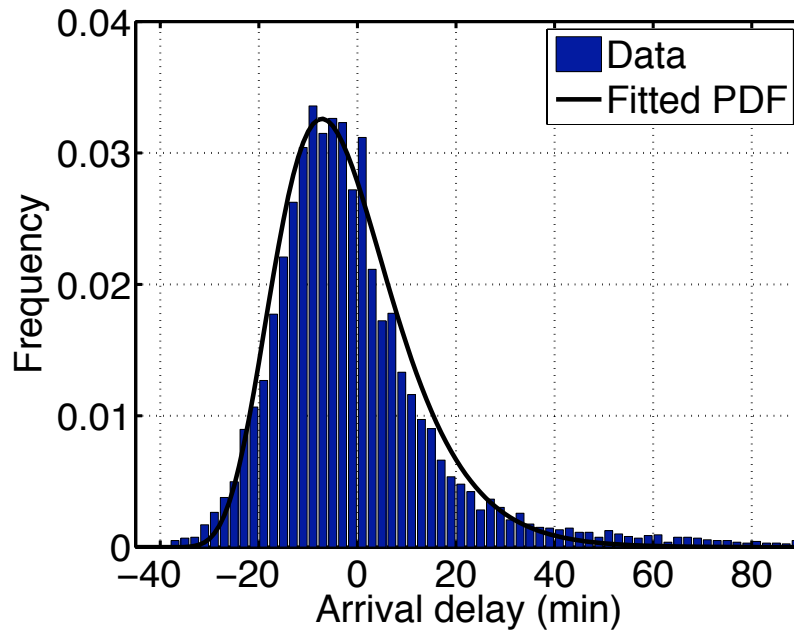
Figure 5: Arrival Delay Distribution of NWA at DTW in March 2006 and the Fitted PDF.

A Log-normal distribution is used to model gate delays. A Log-normal distribution is bounded to nonnegative numbers, but delays can have negative values (early

departure or arrival). So, a shift parameter is necessary to capture the characteristic of delays. The probability density function (PDF) of shifted Log-normal distribution is given in Equation (2), where c is the shift parameter. Parameters of fitted PDFs for departure and arrival delays of NWA at DTW in March 2006 are given in Table 1, and the fitted PDFs are shown in Figure 4 and Figure 5.

$$X \sim \mathbf{Log}-\mathcal{N}(\mu, \sigma) + c, \tag{1}$$

$$f_X(X; \mu, \sigma, c) = \frac{1}{(X-c)\sigma\sqrt{2\pi}} e^{-\frac{(\ln(X-c)-\mu)^2}{2\sigma^2}}, \forall X > c. \tag{2}$$

Table 1: Parameters of the Fitted PDFs

	μ	σ	c
Departure Delay	1.802	1.242	-5.275
Arrival Delay	3.812	0.2814	-49

It is interesting that many departing flights departed earlier than schedule as shown in Figure 4. In order to see whether it happened only at DTW or not, gate delays of Delta Airlines (DAL) at Hartsfield-Jackson Atlanta International Airport (ATL) in May 2011 are shown in Figure 6 and Figure 7. It is shown that many departures at ATL also departed earlier than schedule according to the airline on-time statistics provided by BTS [14].
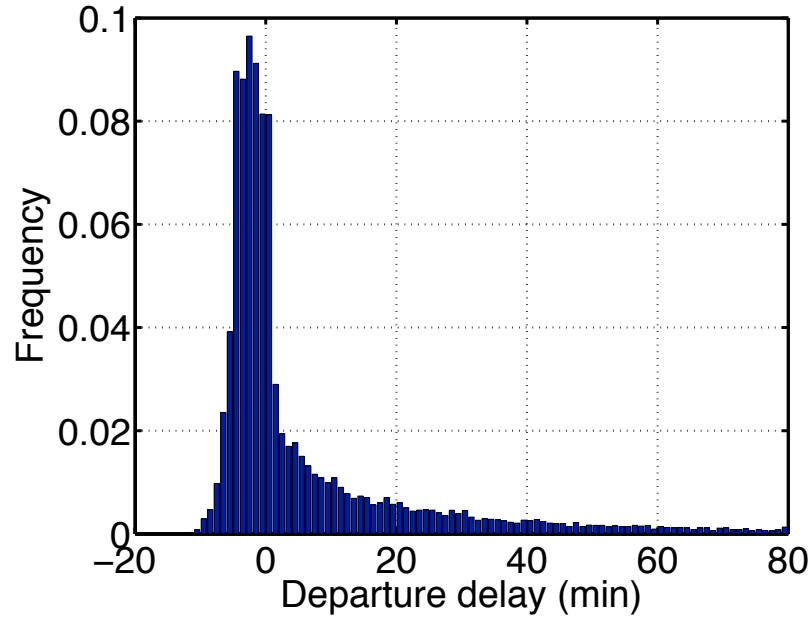
Figure 6: Departure Delay Distribution of DAL at ATL in May 2011.
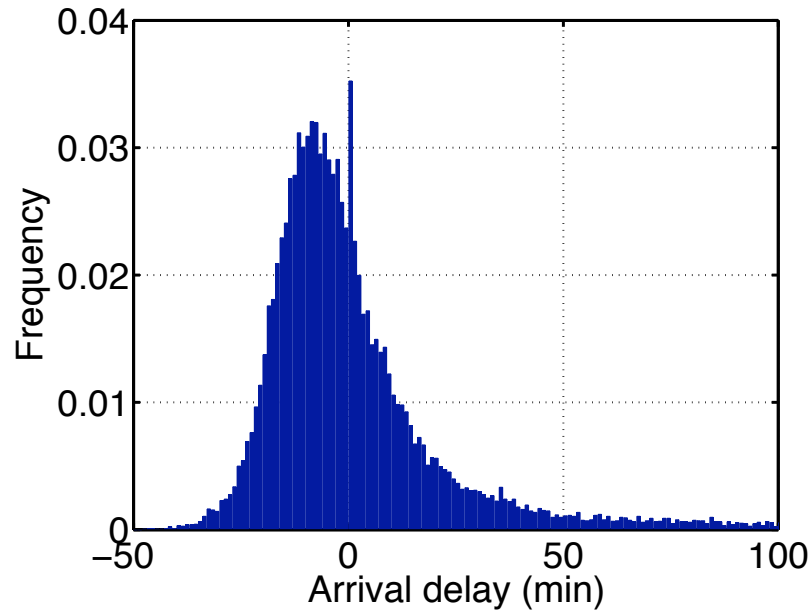
Figure 7: Arrival Delay Distribution of DAL at ATL in May 2011.

1.3.2 Delay Propagation Model

In addition to the analysis of gate delays, the analysis of delay propagation in the turn around process is important to understand gate operations. An aircraft that

arrives late is most likely to depart late, too. However, more precise knowledge of the interrelationship between arrival delay and departure delay is necessary. Shumsky studied the turn around process and suggested a turn model [61]. He assumed that a gate departure delay depends on "available turn time." He defined the available turn time as the time remaining after an aircraft arrives at a gate until its scheduled departure time. So, the available turn time is $sch_d - act_a$, where sch_d denotes the scheduled departure time and act_a denotes the actual arrival time. The turn model proposed by Shumsky is given in Equation (3). The quantity dly_d is the departure delay, C is a fixed amount of departure delay applied to every aircraft, b is an additional departure delay ratio due to insufficient available turn time, m is a minimum turn time, and e is residual. According to Shumsky's model, there is a minimally required turn time, and an arrival delay is propagated to the corresponding departure delay when the available turn time is shorter than the minimum turn time (m).

$$dly_d = C + b * \max(0, m - (sch_d - act_a)) + e. \tag{3}$$

In order to analyze delay propagation, each arrival should be paired with the following departure that uses the same aircraft. The following departure is called the tail of the arrival. Because published data are separated into arrival data and departure data, tail numbers are used to identify aircraft. Applying this procedure to the NWA data at DTW in March 2006, 7545 arrival-departure pairs are identified, and 1072 pairs of them with a turn time shorter than 20 minutes or longer than 200 minutes are filtered out. It is considered that a turn time shorter than 20 minutes is not in normal operational conditions and a turn time longer than 200 minutes is not meaningful for the analysis of delay propagation because a departure delay after a large turn time (i.e., longer than 200 minutes) can be thought to be independent from the previous arrival delay. Then, 8 arrival-departure pairs are filtered out because their actual turn times are shorter than 20 minutes, which seems extraordinary. The

distribution of scheduled turn times of 6465 arrival-departure pairs is shown in Figure 8. Most arrival-departure pairs are scheduled with turn times shorter than 100 minutes, and the majority of the turn times range from 50 minutes to 70 minutes.
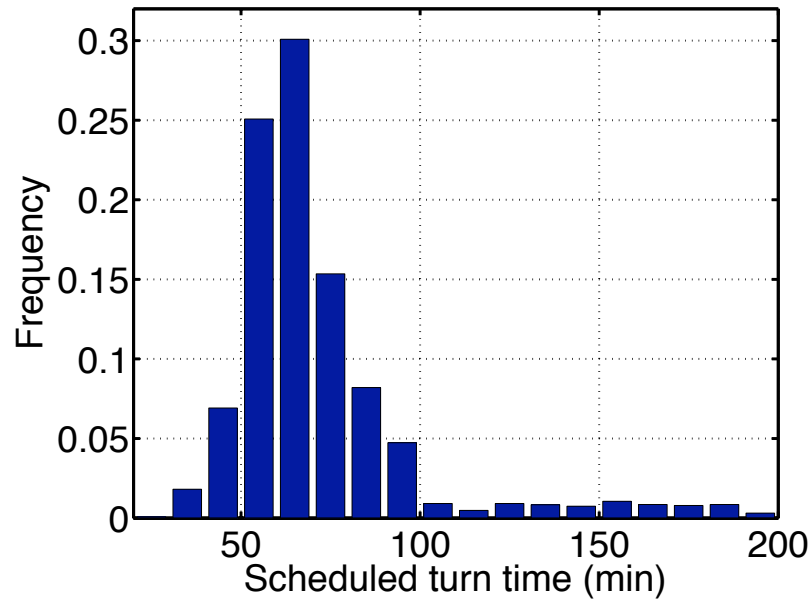
Figure 8: Distribution of Scheduled Turn Times of NWA at DTW in March 2006.

Shumsky's model is applied to the data and shown in Figure 9. Parameters of the delay propagation model are given in Table 2. It is shown that the minimum required turn time of the data is 48 minutes and every minute of an arrival delay above the minimum is propagated to 0.96 minutes of a departure delay.
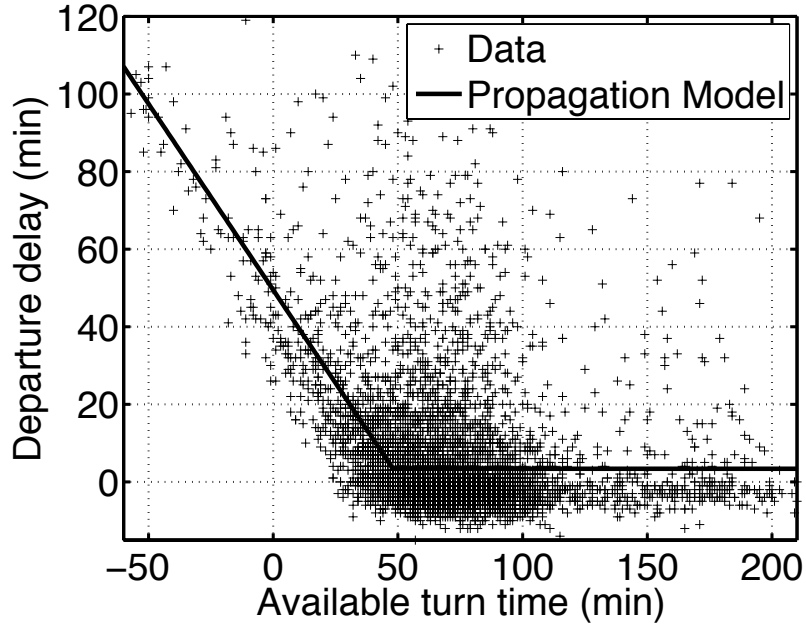
Figure 9: Delay Propagation Model for NWA at DTW in March 2006.

Table 2: Parameters of Delay Propagation Model for NWA at DTW in March 2006

m	C	b
48	3.379	0.96

1.4   Collaborative Ramp Management

Airport Collaborative Decision Making (A-CDM) was initiated by IATA and EURO-CONTROL in 2007, aiming at improving system predictability, reducing taxi times and delays, and enhancing resource management by sharing highly accurate data of aircraft readiness (estimates of arrival and departure times) [43]. With the enhanced estimation of readiness, A-CDM helps air traffic controllers optimize the sequence of departures, which results in reduced taxiway congestion, saving in fuel burn, and reduced emissions and noise. The implementation of A-CDM is one of the five action points of the Flight Efficiency Plan of IATA, EUROCONTROL, and CANSO [43]. In the U.S., the CDM-based Ground Delay Program (GDP) was introduced

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[7]. The GDP is a traffic flow initiative to "control air traffic volume to airports where the projected traffic demand is expected to exceed the airport's acceptance rate for a lengthy period of time. Lengthy periods of demand exceeding acceptance rate are normally a result of the airport's acceptance rate being reduced for some reason. The most common reason for a reduction in acceptance rate is adverse weather such as low ceilings and visibility."[30] The GDP is also based on accurate shared data of estimates of arrival and departure times. The CDM concept has been implemented and evaluated in some U.S. airports. For instance, Collaborative Departure Queue Management (CDQM), which was field-tested at Memphis International Airport, manages the runway queue size and shifts some queueing time at the runway to the gate or ramp area [12]. CDQM assigns a number of allocation slots to enter the taxiway system for departures and allows the airlines to manage the sequence of their flights flexibly. Another example of CDM was tested at New York John F. Kennedy International Airport [56]. Both examples are supposed to reduce congestion on an airport surface by holding departures at gates or holding pad when the taxiway and runway system is congested and the throughput of the runway is saturated [61, 59, 4]. Recently, Simaiakis et al, field-tested pushback rate control at Boston Logan International Airport [63]. In Europe, CDM has been implemented at Munich Airport [54], Brussels Airport, Frankfurt Airport, London Heathrow Airport, and Paris Charles De Gaulle Airport [28]. However, there is still a growing need for more efficient and more robust tools to improve operations at congested airports. In particular, we believe that this effort should be combined with a necessary shift towards a better understanding of passengers' interests and concerns.

Most CDM-based approaches, such as the GDP and the gate-holding policy (or departure metering), let some departures stay at the gates or parking spot. As a result, the corresponding gates are occupied over the scheduled time, and the following flights cannot access the gates until the gate-held flights are cleared. So, they

can cause a shortage of available gates and gate conflicts, which induces delays and other congestion in the ramp area. The GDP and departure metering policy are activated during peak times of the day when airlines compete with each other for departure slots because departure demand generally outnumbers the available departure slots during peak times. At the same time, the airlines need to secure as many available gates as possible in order to accommodate incoming flights. Consequently, the airlines want to push their departures into the congested taxiway queue. However, this would increase taxi-out delays and emissions on airport surface. In order to manage a congested airport and satisfy various stakeholders, information sharing and collaboration between airport authorities and airlines is necessary. Moreover, gate assignments need to be ready and robust to accommodate extra gate occupancy times or gate-held times caused by the GDP or departure metering. The airlines plan gate assignments before the actual operations. So, they consider the weather forecast, demand analysis, and other issues that may influence the flight schedules and try to minimize the impact of uncertain delays or operational delays on the flight schedules. Also, the airlines want to circulate gate usages as compactly as possible so that they can operate the maximum number of flights given the fixed number of gates while minimizing disturbances of gate assignments such as gate reassignments.

Future research on gate assignments needs to address passengers' experience and collaborative ramp management as well as traditional considerations such as walking distance of passengers. To tackle these issues, a better understanding of passengers' concerns and collaboration of stakeholders are necessary.

1.5 Research Questions and Contributions

This dissertation will answer the following research questions.

Question 1. What is the impact of gate assignment on ramp congestion, and how can we improve the efficiency of traffic flow on the ramp by proper gate assignment?

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Question 2. How can we concurrently satisfy various objectives of gate assignment such as minimizing passengers' transit time, maximizing the robustness of gate assignment, and improving the efficiency of traffic flow on the ramp?

Question 3. What is the impact of gate assignment on departure operations, and how can we improve the efficiency and flexibility of airport operations by proper gate assignment?

Traditional gate assignment research focuses on the accommodation of passengers' demands and the robustness of gate assignment. For example, one of the main objectives of the GAP is to minimize the total walking distance of passengers [52, 38]. Gate assignment affects taxi trajectories of aircraft as well as walking trajectories of passengers. In addition, the taxi trajectories of aircraft are closely related to interferences between aircraft on the ramp, which cause ramp congestion. Therefore, ramp congestion should also be considered when gates are being assigned. However, ramp congestion had not been considered as an important objective of the GAP. Cheng investigated interferences occurring between two adjacent gates [22]. For instance, he considered a pushback delay that is caused by an arrival to the next gate. However, the scope of ramp congestion in his research is limited to what happens between adjacent gates. This dissertation investigates congestion on the overall ramp area caused by movements of aircraft and analyzes the extent to which gate assignment impacts ramp congestion. Consequently, this dissertation contributes to airport research by suggesting a promising improvement of the efficiency of traffic flow on the ramp through proper gate assignment.

There are a number of objectives of gate assignment such as minimizing passengers' walking time [52, 38] and maximizing the robustness of gate assignment [9, 10, 51]. In addition to these objectives, this dissertation proposes a new perspective that takes aircraft movement and ramp congestion into account. The majority of previous research on the GAP tried to optimize a single objective. This dissertation

investigates the relationships and the trade-offs between various objectives of gate assignment. Moreover, this dissertation contributes to gate assignment research by proposing a strategy that balances three objectives of gate assignment at the same time. As a result, passengers can move faster to their destinations at an airport (e.g., the gate of the connecting flight, baggage claim, etc.), delays on the ramp are reduced, and more arriving aircraft can access their gates without waiting until the gates become available.

Gate assignment does not influence only the efficiency of passenger movement and traffic flow on the ramp, but also the flexibility of ramp operations. For instance, the departure metering holds some departing aircraft at gates so that the airport surface becomes less congested. However, if a gate that is holding a departure is requested by an arrival, the departure needs to be released from the gate; otherwise the arrival waits for an available gate. Such a situation is called gate conflict, and the probability of a gate conflict is affected by gate assignment. Therefore, gate assignment is critical to the functionality of departure metering. This dissertation analyzes the impact of gate assignment on departure operations through departure metering. By this analysis, this dissertation contributes to airport research by providing a strategy that improves the efficiency of departure operations at congested airports with limited gate resources.

1.6   Outline of this Dissertation

This dissertation is organized as follows. Chapter 2 describes ramp operations and ramp congestion. In chapter 2, observation data of the ramp areas at Hartsfield-Jackson Atlanta International Airport are provided, and aircraft movements are modeled both in nominal operational conditions and in disturbed conditions based on the observation data. In addition, two distinguishable categories of ramp congestion are illustrated. Chapter 3 deals with the gate assignment problem (GAP). Traditional

objectives of the GAP are discussed, and a new perspective (objective) of the GAP is presented that takes ramp congestion, which is demonstrated in chapter 2, into account. So, chapter 3 addresses the first research question. A numerical formulation and a meta-heuristic algorithm for the GAP are also given in chapter 3. Chapter 4 analyzes the trade-offs between the objectives that are presented in chapter 2 and answers the second research question. Two illustrative numerical examples are used for the analysis of the trade-offs. Moreover, a real-world gate assignment at a major U.S. hub airport is compared with an optimized gate assignment that is proposed in this dissertation. Chapter 5 tackles the third research question. In chapter 5, two airports' departure processes are modeled and simulated. Using the current gate assignment and a proposed optimized gate assignment, the impact of gate assignment on departure metering is analyzed. In addition, a scheme towards total airport control that accounts for passengers' experience, efficient operations, and collaboration of stakeholders is proposed. Chapter 6 summarizes the findings of this dissertation and proposes the direction of future research.

CHAPTER II

RAMP OPERATIONS AND RAMP CONGESTION

2.1 Introduction

Airport operations range from landing to take-off of an aircraft as shown in Figure 2. After an aircraft lands, it taxies into a ramp area and parks at a gate. While the aircraft is docked at the gate, passengers disembark and board the plane. When the aircraft is ready to depart, it pushes back and taxies out to a runway. Then, the aircraft takes off. To enhance the understanding of airport dynamics and improve the efficiency of airport operations, many studies have been conducted, and most of them focus on runway and taxiway operations. Idris et al. observed departure processes at Boston Logan International Airport and analyzed the impact of the runway, gates, ramps, and the taxiway system on the efficiency of the departure flow [44]. They concluded that the take-off queue at the runway is the main source of departure delays. Balakrishnan and Jung presented a model that simulates taxiway operations at Dallas/Fort Worth International Airport [6]. Their study is about optimizing taxi routes on the airport surface to reduce taxi delays.

Among airport operations, this chapter aims to model ramp operations. Ramp operations are complicated due to the interactive nature of the operations. Except for some airports, where aircraft are pushed back directly to the taxiway, the ramp area is separated from the taxiway and is shared by both inbound and outbound traffic. Moreover, sometimes on ramps an aircraft prevents another aircraft from taxiing [46]. This situation is observed only in limited areas outside ramps such as the crossing point of two runways, the merging point of two taxiways, etc. There have been relatively few studies of ramp operations in air transportation research, but they

are important in improving airport operations. For instance, Idris et al. found that the majority of arrival delays on airport surface happen when an aircraft has landed but the assigned gate is still occupied by another aircraft [44]. So, if gate operation becomes more efficient and robust against disturbance, airport operations also become more efficient by reducing arrival delays. Departure metering also has an impact on the efficiency of airport operations; it reduces congestion on the taxiway and the runway by controlling the number of pushbacks [4, 63]. Holding departing aircraft at their gates is closely related to gate and ramp operations. Cheng introduced a rule-based simulation model that describes the network effect of gate operations [21]. His model captures a delayed departure caused by the delay of an arrival sharing the same aircraft, a delayed arrival caused by the delay of a departure sharing the same gate, etc. However, there is no model that describes details of ramp operations focusing on aircraft movement.

2.2 *Observation at Hartsfield-Jackson Atlanta International Airport*

This chapter proposes a detailed model of ramp operations based on observations at Hartsfield-Jackson Atlanta International Airport. A model for ramp operations should be specific to a corresponding airport based on observations because most details of ramp operations depend on the geometrical and operational characteristics of the ramp area at the airport. The Atlanta airport is the world's busiest airport in terms of the number of passengers and operations. There are 5 runways and 7 concourses. The last concourse, F, for international flights was opened in May, 2012. The ramp area of the Atlanta airport consists of 9 ramps as shown in Figure 10. From ramp 1 to ramp 5, there are 2 parallel taxi lanes that can be used bidirectionally. At both ends of each taxi lane, there is a spot, which is an entry point from the taxiway. Because the taxi lanes are along the north-south direction, two spots of a ramp are located on the northern boundary of the ramp and the other two spots are located

on the southern boundary. In general, aircraft use the taxi lane and the spot closer to their gates. Figure 11 shows the ramp 2 at the Atlanta airport. Two black dashed lines represent two bidirectional taxi lanes and spots are marked by circles with names. N1 and N2 indicate the two northern spots, and S1 and S2 indicate the two southern spots. Suppose that an aircraft taxies from the taxiway on the south side to a gate of concourse A. Then, the arrival enters the ramp 2 through the spot S1. The spot for a departure is not necessarily the same as the spot for an arrival. For instance, if the aircraft uses a runway on the north end for departure, it exits the ramp through the spot N1.
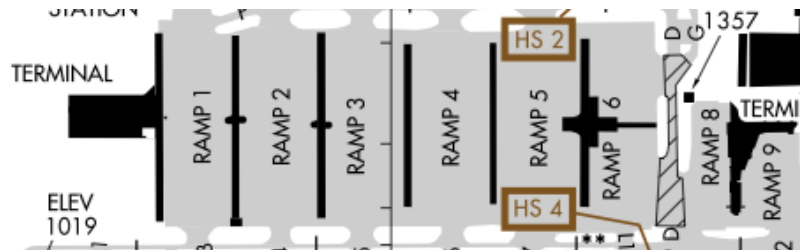
Figure 10: Ramp Areas at Atlanta Airport.
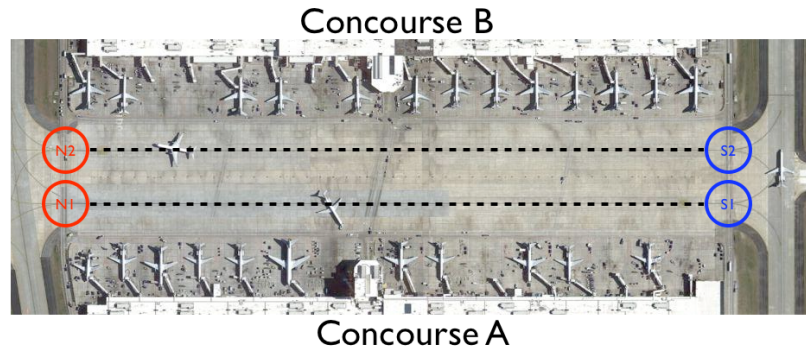
Figure 11: A Satellite Picture of Ramp 2 at Atlanta Airport: N1 and N2 indicate two spots on the northern boundary, and S1 and S2 indicate two spots on the southern boundary.

Observations were made at the Atlanta airport during several days in June, 2012 using the clearance given by Delta Airlines. The observations included measuring the duration from when an aircraft begins pushback to when the aircraft begins

moving by its own power. Over 120 pushbacks were observed and measured during the observation period. In addition, delays due to interference between movements of aircraft were observed and measured. Based on those observations, this chapter proposes a model that captures ramp operations in nominal conditions as well as in situations when movements of aircraft are interrupted by other aircraft.

2.3 Nominal Ramp Operations

This section describes nominal ramp operations when there is no disturbance. Ramp operations begin when an aircraft taxies from a taxiway to a spot. The ramp operations for an arrival are as follows.

1. An aircraft taxies to a spot.

2. The aircraft calls the ramp tower for clearance to access the ramp.

3. The ramp tower clears the aircraft if there is no vehicle or other aircraft preventing the aircraft from taxiing into the ramp.

4. The aircraft taxies to the gate and parks.

After a certain turn-around time, the aircraft is ready to depart. The ramp operations for a departure are as follows.

1. An aircraft is ready to push back and it calls the ramp tower for clearance for pushback.

2. The ramp tower gives the pushback clearance if there is no vehicle or other aircraft preventing the aircraft from pushing back.

3. The aircraft pushes back.

4. The aircraft calls the ramp tower for clearance for taxiing on the ramp.

5. The ramp tower gives the taxi clearance if there is no vehicle or other aircraft preventing the aircraft from taxiing.

6. The aircraft taxies to a spot and calls the Airport Traffic Control Tower (ATCT) for clearance to enter the taxiway.

7. The ATCT clears the aircraft, and the aircraft is on the taxiway.

Once the aircraft reaches a spot, the control of the aircraft is taken over from the ramp tower by ATCT. Thus, ramp operations finish when the ATCT controls the aircraft. At the Atlanta airport, ramp towers are operated by airlines and a third-party company. In contrast, the ATCT is operated by the FAA. The pushback procedure is as follows.

1. An airport tug approaches the aircraft and connects the towbar to the aircraft.

2. The airport tug pushes the aircraft back.

3. The airport tug disconnects the towbar.

4. The aircraft calls the ramp tower for clearance to taxi on the ramp.

While an aircraft is parking or pushing back, two wing-watchers follow the aircraft on each side to ensure the wings of the aircraft do not touch other aircraft or airport facilities.
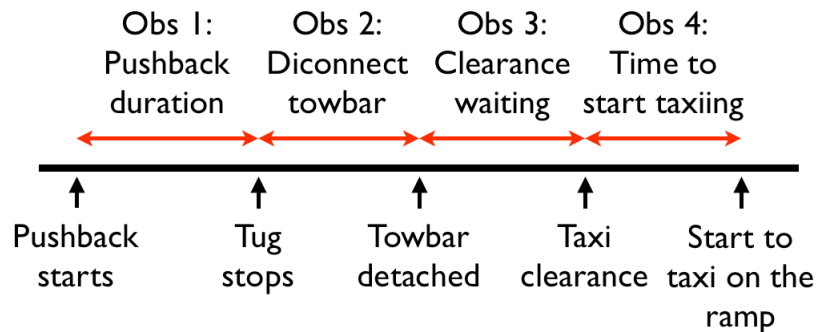
Figure 12: Observed Durations in Pushback Procedure.

During the observation period, 5 time points in the pushback procedure were recorded. The first time point is when the airport tug starts to push the aircraft back. The second time point is when the airport tug stops. The third time point is when the towbar is disconnected. The fourth time point is when the ramp tower gives the taxi clearance on the ramp. The last time point is when the aircraft actually starts to taxi. Consequently, 4 durations were obtained from the time points, and they are presented as follows.
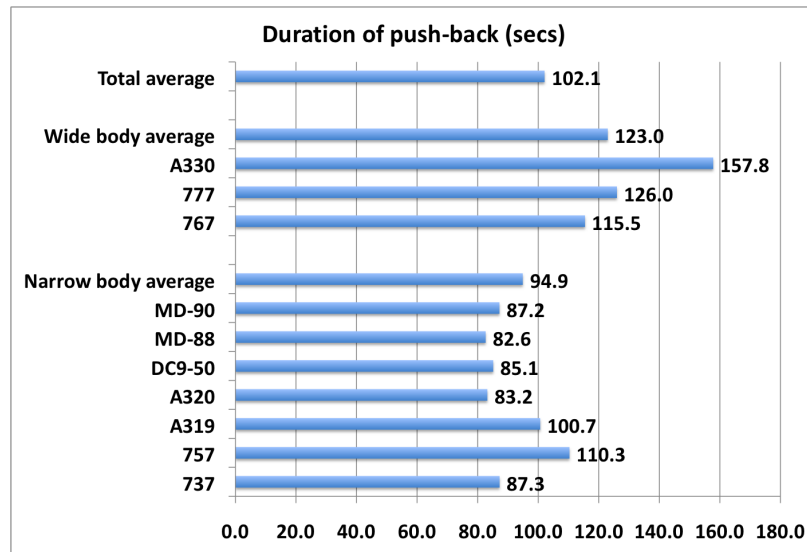
Figure 13: Duration of Pushback per Fleet Type.
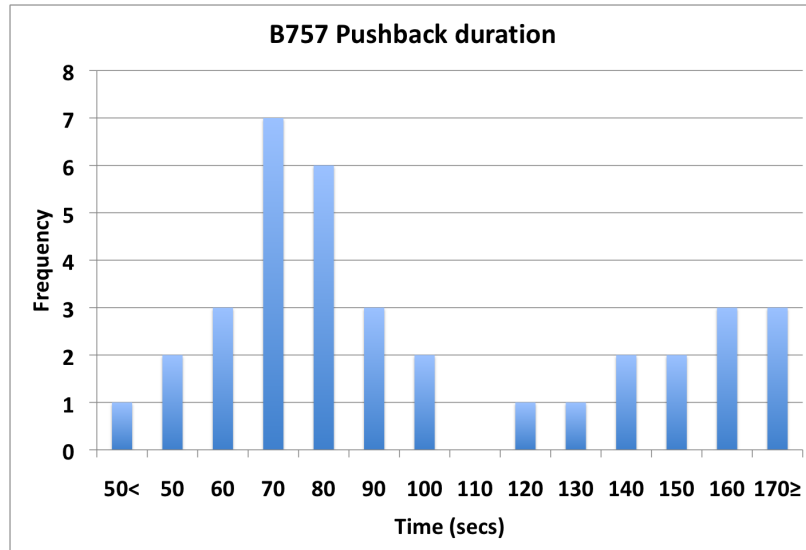
Figure 14: Distribution of Pushback Duration of B757.

Figure 13 shows the durations of pushback. Fleet types are categorized as wide body and narrow body. Apparently, wide body aircraft take a longer time to push back (123 seconds) than narrow body aircraft (94.9 seconds). Also, the pushback duration differs according to fleet types, but the sample size of each fleet type varies. The most frequently observed fleet type is Boeing 757 with 36 out of 121 flights. On the other hand, Boeing 777 was observed only twice during the observation period. Therefore, it is hard to determine the average pushback duration statistically, but the data give us an approximate knowledge of pushback duration. The total average of pushback duration is 102.1 seconds, but several instances of delayed pushback were observed. On two occasions, the towbar was disconnected during pushback, and the corresponding durations of pushback were 221 seconds and 282 seconds. Both occurred while a B757 was being pushed back, and the average pushback duration of a B757 is 110.3 seconds. Consequently, the disconnection of the towbar during pushback procedure increases the pushback duration by about 2-3 minutes. The distribution of pushback duration of B757 is given in Figure 14. It is shown that the majority of B757 finished pushback in 2 minutes and the distribution is similar

to a Normal distribution. It is also shown that some B757 took a longer time to push back, and two of them were caused by the accidentally disconnected towbar during pushback. The others happened at gates in the finger of concourse E. Because pushback trajectories from the finger of concourse E are complicated and long, the pushback duration is also increased. Therefore, the pushback duration also depends on the distance to push back. For instance, Delta Airlines flight DL 66 on June 16, 2012 pushed back from gate E18, which is located in the finger of concourse E, and the pushback distance was not short. So, the pushback duration was 187 seconds, which is 71.5 seconds longer than the average duration of B767. Sometimes, a very slow pushback happened, though this was rare. For instance, Delta Airlines flight DL 114 on June 29, 2012 pushed back for 241 seconds.

Duration to disconnect towbar (secs)

Total average	40.5
Wide body average	40.3
A330	41.0
777	38.0
767	40.4
Narrow body average	40.5
MD-90	40.8
MD-88	40.3
DC9-50	48.6
A320	40.4
A319	47.0
757	40.3
737	33.8
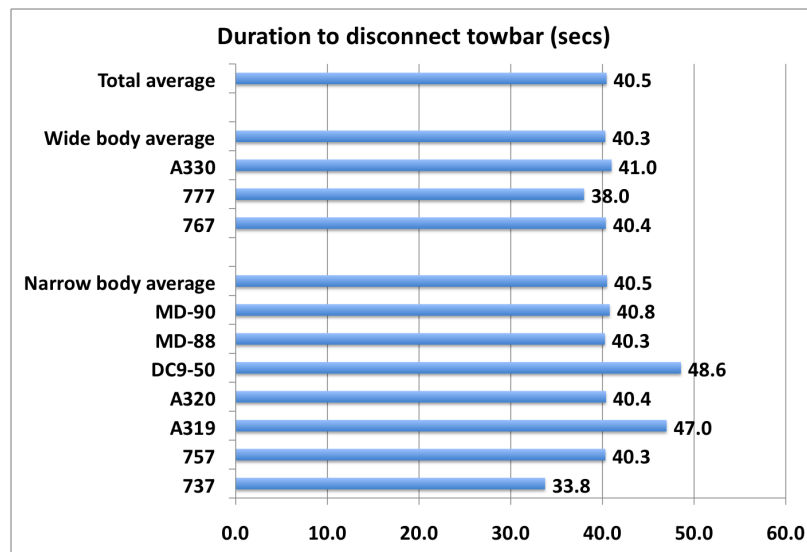
Figure 15: Duration to Disconnect Towbar per Fleet Type.

Figure 15 shows the duration of disconnecting the towbar after pushing an aircraft back. There is no significant difference among fleet types. It was observed twice that the towbar became stuck during disconnection, and the corresponding durations of disconnection were 352 seconds and 147 seconds. We conclude that disconnecting the towbar takes about 40 seconds on average regardless of fleet type.

Figure 16: Distribution of Waiting Time for Taxi Clearance.

Figure 16 shows the distribution of waiting time for taxi clearance. The distribution is similar to a Normal distribution. The horizontal axis represents the lower bound of each bin. So, the first bin is from 20 seconds to 24 seconds, and the last bin accounts for a wait time of longer than 80 seconds. The taxi clearance is issued depending on the current congestion of the ramp. Thus, it is independent of fleet types. The average waiting time is 47.7 seconds, and the standard deviation is 11.9 seconds. As shown in Figure 16, most aircraft are cleared to taxi in 35-60 seconds.
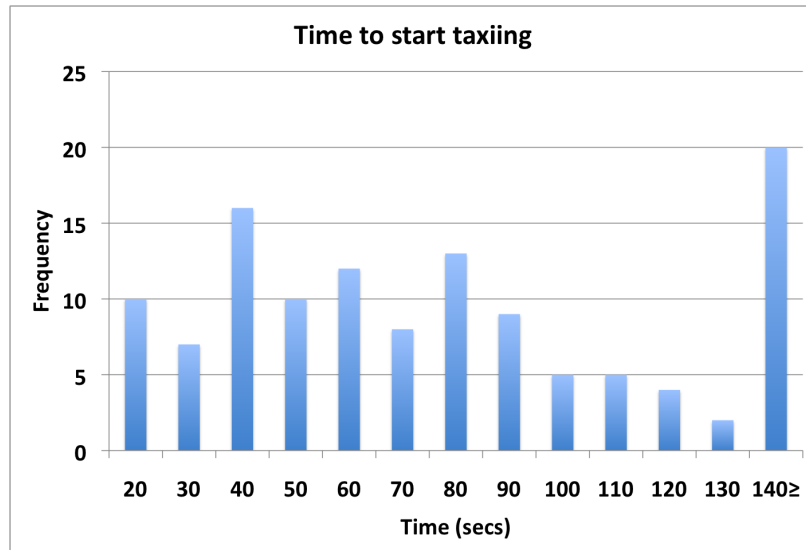
Figure 17: Time to Start Taxiing.

Figure 17 shows the duration from when an aircraft is cleared to taxi to when it actually starts taxiing. Unlike Figure 16, the time to start taxiing is scattered: the average is 93.1 seconds and the standard deviation is 71 seconds. It is notable that there are so many late starts (longer than 140 seconds). These late starts are caused mostly by congestion on the ramp. For example, a parking aircraft prevents a nearby aircraft from moving. Also, there were some late starts without any apparent congestion on the ramp. In general, pilots go down checklist after pushback and call for taxi clearance. The late starts without apparent congestion would be caused by pilot's checklist if he calls for taxi clearance before he finishes the checklist.

2.4 Ramp Congestion

Ramp congestion caused by physical conflicts increases flight delays and consequently reduces the efficiency and capacity of airport ramp operations. The first thing to consider is the ramp geometry and physical constraints to understand more about ramp dynamics. The horseshoe at Boston Logan International Airport is an example of physical constraints of the ramp area. Figure 18 is a satellite picture of the horseshoe at the Boston airport. Because of the narrow entry of the horseshoe, only one aircraft

can taxi through the entry at any time. In congested airports, departing aircraft form a long queue for take-off clearance and the queue often creates another queue inside a ramp. The queue inside the ramp limits an aircraft's movements and leads to ramp congestion. In addition, pushback procedures require sufficient space for safety and proceed at a lower speed than the usual taxi speed. So, scheduling and timing are important factors for preventing ramp congestion. Also, during peak times, some aircraft are forced to pass another aircraft to avoid incidents when they meet on the same taxi lane. An aircraft in the center of Figure 19 is switching taxi lanes because another aircraft on the left side of the figure is taxiing onto the ramp. Figure 20 shows a ramp area at Hartsfield-Jackson Atlanta International Airport. An aircraft is pushing back in the middle of the right taxi lane, which is indicated by the airport tug, and another aircraft (circled) is taxiing from bottom to top. Because the right taxi lane is blocked by the pushing back aircraft, the taxiing aircraft is switching taxi lanes.
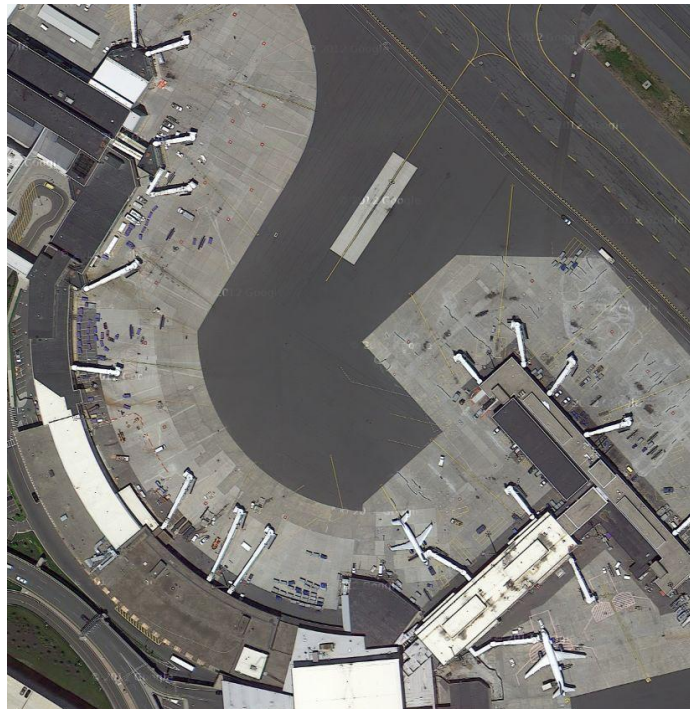
Figure 18: Horseshoe Ramp Area at Boston Logan International Airport: Only one aircraft can taxi through the spot in the horseshoe ramp area.

Figure 19: An Aircraft Passes Another Aircraft at Hartsfield-Jackson Atlanta International Airport.
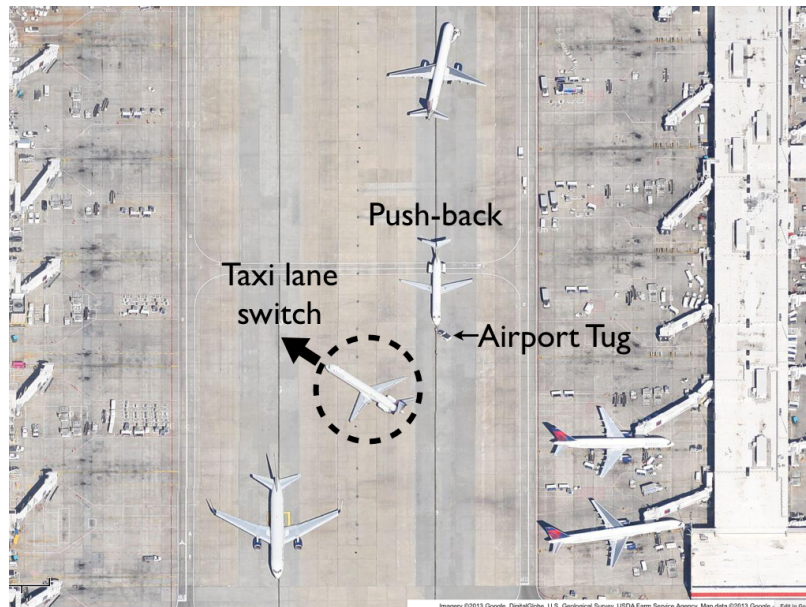
Figure 20: Satellite Picture of Hartsfield-Jackson Atlanta International Airport from Google Maps [35]: There are two parallel taxi lanes, and one aircraft (circled) is taxiing from a taxi lane to another in order to avoid the pushing-back aircraft.

This study distinguishes two types of physical conflicts: pushback blocking and taxi blocking. Pushback blocking is a situation in which an aircraft prevents another

aircraft from pushing back or is delayed due to another aircraft's pushback as shown in Figure 20. An example is illustrated in Figure 21. Suppose that flight f_1 begins pushing back at 10:01:00 and finishes pushback at 10:02:00. After pushback, f_1 stays at node 1 for 90 seconds while it is running its checklist and waiting for a taxi clearance. So, f_1 occupies node 1 from 10:02:00 to 10:03:30. Assuming that flight f_2 needs to pass through node 1 and reaches node 1 at 10:03:00, then f_2 has to wait until f_1 finishes pushback or pass by f_1, which causes a taxi delay.
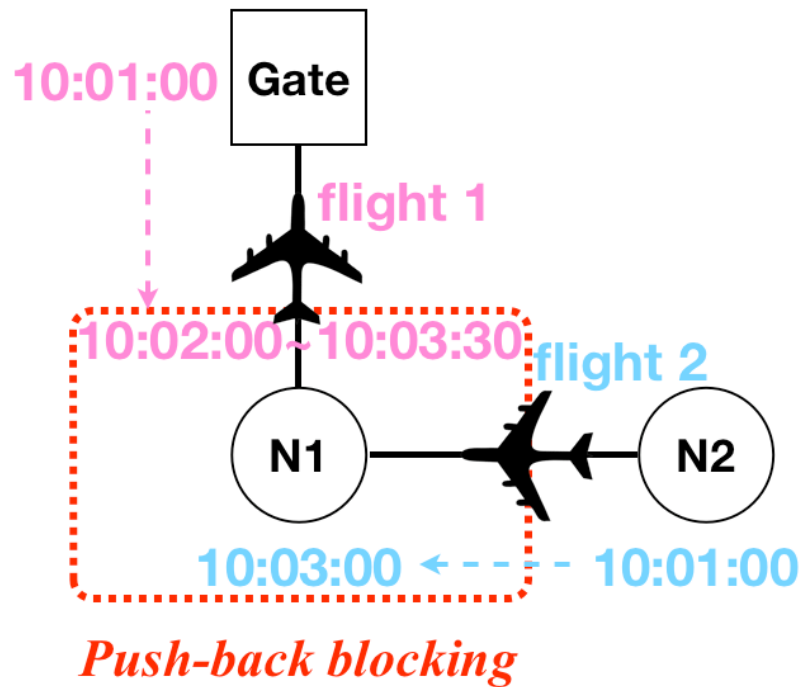
Figure 21: An Illustrative Example of Pushback Blocking.

Taxi blocking occurs when two aircraft taxi in opposite directions and one aircraft blocks the other's taxi route as shown in Figure 19. At Hartsfield-Jackson Atlanta International Airport, each ramp has two bidirectional taxi lanes as shown in Figure 11. Generally, each taxi lane serves the closer concourse, but this rule can be altered if the ramp is congested. If two aircraft taxi on a taxi lane concurrently and in opposing directions, then taxi blocking occurs, as shown in Figure 22. Suppose flight f_1 taxies toward the right and flight f_2 taxies toward the left. Flight f_1 reaches nodes 1, 2, and

3 at 10:01:00, 10:02:10, and 10:04:00, respectively; and flight f_2 reaches nodes 3, 2, and 1 at 10:00:40, 10:02:30, and 10:03:40, respectively. Then f_1 and f_2 meet on the link connecting node 2 and node 3, and one of two flights should change its taxi lane, which causes a taxi delay because switching taxi lanes influences the traffic on both taxi lanes.
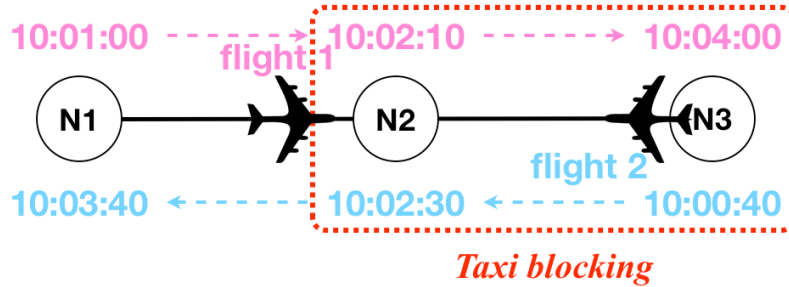
Figure 22: An Illustrative Example of Taxi Blocking.

Pushback blocking and taxi blocking increase taxi time, fuel burn, and emissions.

2.5 *Disturbed Ramp Operations*

This section describes what happens when nominal ramp operations are disturbed by an interference between two aircraft movements. Such disturbances cause delays in ramp operations. The most common disturbance is taxi blocking, which is the situation when two aircraft meet head-to-head on a taxi lane on a ramp. Then, one aircraft must change to another lane. If a departure meets an arrival head-to-head, the departure taxies to another taxi lane, in general. Because arriving flights generally use the closest taxi lane to their assigned gates, if an arrival switches its taxi lane, then the aircraft needs to move back to the original taxi lane in order to park at its gate. On the contrary, a departure is free to switch its taxi lane because it just needs to taxi out of the ramp and there are two spots on each boundary of the ramp as shown in Figure 11. Although most arrivals use the closest taxi lane, it was also observed five times that an arrival entered the ramp through the opposite taxi lane

and crossed another taxi lane to park at its gate. Forty-six instances of switching taxi lanes were observed out of 470 flights during the observations. It was observed that narrow body aircraft, e.g., CRJ, switched taxi lanes more often than wide body aircraft when a narrow body and a wide body aircraft were in conflict. Because a narrow body aircraft is much smaller, it is more maneuverable. Although it is uncommon for an aircraft to switch taxi lanes twice, that was observed 14 times, and two of them were arriving flights. In most of those cases, the aircraft that switched twice was a narrow body aircraft. In addition to switching, parking delays were also observed. From time to time, an aircraft's movement prevented another aircraft from parking at a gate. Table 3 shows observation data on disturbed ramp operations. Note that numbers in parentheses in the fifth row represent the number of arrivals that switched taxi lanes. For example, 15 aircraft switched taxi lanes on July 14, 2012 and one of them was an arrival. On July 7 and 8, 2012, it was not recorded whether the aircraft was arriving or departing.

Table 3: Observations of Disturbed Ramp Operations

Date	July 7	July 8	July 14	July 15
Time	9am-	12pm-	10am-	9am-
	3pm	6pm	4pm	3pm
Concourses	A-B	B-C	A-B	D-E
Estimated number of total operations	130	110	150	80
Number of lane switch	12	9	15 (1)	10 (4)
Average delay due to lane switch	32.1 s	24.2 s	29.8 s	35.4 s
Number of parking delays	4	3	5	3
Average parking delay	146.3 s	240 s	133.2 s	204.3 s

There were a few other delays such as waiting for baggage carts, but they were not significant enough to include at approximately 10 seconds each. Based on the

observations, it seems that about 70% of delays were due to taxi blocking, and the average delay caused by taxi blocking was about 30 seconds for the aircraft that did not change taxi lanes. The maximum delay due to taxi blocking was about a minute. It was also observed that two aircraft departed simultaneously from the next gate, and in this case, a maximum 5-minute delay was added. Sometimes, an aircraft had to wait for another aircraft ahead of it to park, which caused about 30 seconds of delay.

2.6   Conclusion

This chapter described aircraft movement on the ramp area at Hartsfield-Jackson Atlanta International Airport. In nominal conditions, an aircraft enters a ramp with a clearance from a ramp tower, stays at a gate during a certain turn-around time, pushes back with a clearance from the ramp tower, and taxies out to the taxiway with a clearance from the airport tower (ATCT). The detailed pushback procedure is presented, and the duration of each step of the procedure was observed. From the observation, it is concluded that pushback duration depends on fleet type, and there is a difference in pushback duration between narrow body and wide body aircraft. On the other hand, the waiting time for taxi clearance is independent of fleet type and is determined by the congestion level of the ramp. When an aircraft interrupts another aircraft's movement, a delay occurs. Most delays happen when two aircraft taxi in opposite directions. In this situation, one aircraft, usually a departing aircraft, needs to switch to another taxi lane. The switching causes a delay of about 30 seconds. In addition, other delay-causing situations were observed such as parking delay due to an aircraft's movement, simultaneous departures from the next gate, etc. This chapter contributes to airport research by providing a ramp operation model based on observation data at an airport. The presented model helps us better understand the complicated movements of aircraft on ramps.

CHAPTER III

AIRPORT GATE SCHEDULING FOR PASSENGERS, AIRCRAFT, AND OPERATIONS

3.1 Introduction

As important resources, airport gates serve passengers who are boarding and disembarking from aircraft. Once a gate is assigned to an aircraft for a given time slot, it cannot be reassigned to another aircraft during that period. Therefore, the appropriate utilization of airport gates is significant to the efficiency of ramp operations. Also, terminals are filled with thousands of passengers, and the flow of passengers in terminals is an important metric of passengers' experience in the airport. In addition, robustness is as important as efficiency of ramp operations. All components in the air transportation system are connected to form an interactive network. So, a disturbance that occurs in one component such as a severe delay at an airport can influence the entire network. For example, a severely delayed departure releases the gate late, and it leads to a delay of the following arrival that is also assigned to the gate. Hence, delays are easily propagated from a flight to another through gates, but the propagation can be reduced if gate assignments are robust against stochastic delays. As a result, gate assignment is significant in reducing passenger delays, relieving ramp congestion, and making ramp operations robust against stochastic delays.

This chapter presents three objectives of gate assignment problem (GAP) and an effective optimization technique to solve the GAP. The first objective is a traditional approach to the GAP that is mainly concerned with minimizing the transit time of passengers through the passenger terminal. The second objective deals with the congestion in the ramp area caused by the interferences between aircraft movements,

which has barely been considered in the GAP research. The last objective maximizes the robustness of gate assignment. Then, a meta-heuristic algorithm is introduced to get a near-optimal solution within a reasonable time.

3.2 Objective 1: Minimize Passenger Transit Time

Previous research on the GAP studied passenger walking distances [52, 38]. Passenger transit time depends monotonically, but not linearly, on walking distance. Indeed, there are many ways to speed up passengers' transit. For instance, all large airports provide passengers with moving walkways for faster transit within the same terminal and buses for faster transit between distant terminals. Hartsfield-Jackson Atlanta International Airport utilizes subway systems to facilitate passenger transit from terminal to concourses and among concourses. Such facilities assist passengers in reducing their transit time. To reflect this reality, a link-node map of passenger areas is generated, and different average moving speeds are applied according to the type of equipment for each link. For example, passengers can move much faster on a link where they can use the subway than on another link where they walk.

The first objective is to minimize the transit time of passengers. Three types of passengers are taken into account: origin, destination and transfer passengers. Origin passengers are passengers departing from the airport, and destination passengers are those arriving at that airport as their final destination. Transfer passengers are passengers transferring from one flight to another at the airport. At hub airports, statistics show that there are more transfer passengers than Origin and Destination (O&D) passengers. For instance, in 2009, 64.2% of passengers at Hartsfield-Jackson Atlanta International Airport, one of the world's busiest hub airports, were there to board connecting flights [5].

The transit time of origin passengers depends on the distance from a security checkpoint to a gate j (d_j^{S}). Let v^{m} denote the average moving speed, which varies

with the configuration of passenger terminal: v^{m} is higher where passengers can move faster by taking moving walkways, underground people mover, etc. Assume that flight i is assigned to gate j and the number of origin passengers of flight i is n_i^{O}, then

$$\text{the total transit time of origin passengers to flight } i \text{ is equal to } n_i^{\mathrm{O}} \times \frac{d_j^{\mathrm{S}}}{v^{\mathrm{m}}}. \qquad (4)$$

Similarly, the transit time of destination passengers depends on the distance from a gate j to a baggage claim (d_j^{b}). Assume that flight i is assigned to gate j and the number of destination passengers of flight i is n_i^{d}, then

$$\text{the total transit time of destination passengers from flight } i \text{ is equal to } n_i^{\mathrm{d}} \times \frac{d_j^{\mathrm{b}}}{v^{\mathrm{m}}}.$$
$$(5)$$

Therefore, the transit time of O&D passengers depends solely on the location of either the departure gate or the arrival gate because the locations of the security checkpoint and baggage claim are fixed.

Unlike O&D flows, every connection flow is related to arrival-departure-gate pairs because connection involves a source and a sink. Therefore, the transit time of transfer passengers depends on the distance between two gates (d_{jl}). Suppose that flight i is assigned to gate j and flight k is assigned to gate l, and let n_{ik} denote the number of transfer passengers between flight i and flight k. Then,

the total transit time of transfer passengers between flight i and flight k is equal to

$$n_{ik} \times \frac{d_{jl}}{v^{\mathrm{m}}}. \qquad (6)$$

Note that the transit time of transfer passengers is related to two flights and two gates, whereas the transit time of O&D passengers is related to one set of a flight and a gate. Consequently, the transit times of O&D passengers are expressed by linear terms of the decision variable (x_{ij}) and the transit times of transfer passengers are expressed by quadratic terms of two decision variables $(x_{ij}$ and $x_{kl})$ in Equation (7).

The first objective is expressed as

$$\text{Obj}_{\text{transit}} = \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} (n_i^{\text{o}} \frac{d_j^{\text{s}}}{v\text{m}} + n_i^{\text{d}} \frac{d_j^{\text{b}}}{v\text{m}}) \; x_{ij} + \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} \sum_{k \in \mathcal{F}, k>i} \sum_{l \in \mathcal{G}} n_{ik} \frac{d_{jl}}{v\text{m}} \; x_{ij} \; x_{kl}, \quad (7)$$

and mathematical formulation of the GAP for the first objective is given below

$$\text{Minimize Obj}_{\text{transit}} \qquad\qquad (8)$$

subject to

$$\sum_{j \in \mathcal{G}} x_{ij} = 1, \; \forall i \in \mathcal{F}, \qquad\qquad (9)$$

$$(t_i^{\text{out}} - t_k^{\text{in}} + t^{\text{buff}})(t_k^{\text{out}} - t_i^{\text{in}} + t^{\text{buff}}) \leq M(2 - x_{ij} - x_{kj}), \; i \neq k, \; \forall i, k \in \mathcal{F}, \; \forall j \in \mathcal{G}, \qquad (10)$$

$$x_{ij} \in \{0, 1\}, \; \forall i \in \mathcal{F}, \; \forall j \in \mathcal{G}, \qquad\qquad (11)$$

$$\text{where } x_{ij} = \begin{cases} 1 & \text{if flight } i \text{ is assigned to gate } j \\ 0 & \text{otherwise.} \end{cases}$$

The decision variable x_{ij} indicates whether flight i is assigned to gate j. The sets $\mathcal{F}$ and $\mathcal{G}$ denote the sets of flights and gates, respectively. Two constraints are given in Equation (9) and Equation (10). The first constraint makes sure that every flight is assigned to a single gate. The second constraint constrains two successive gate occupancies, so that they are separated by more than a certain amount of time, which is called buffer time (t^{buff}). The buffer time is used to absorb disturbances of schedule, e.g. stochastic delays, and to ensure the feasibility of the schedule. Two series of gate schedules with different gate separations are illustrated in Figure 23 and Figure 24. Gate separation is the time gap between two consecutive gate occupancies. The variable t_i^{in} indicates the scheduled gate-in time (arrival time) of flight i, and t_i^{out} indicates the scheduled gate-out time (departure time) of flight i. The gate schedules in Figure 23 have a gate separation longer than the buffer time. So, flight i and flight p can be assigned to the same gate. On the other hand, the gate separation in Figure 24 is shorter than the buffer time. Hence, flight i and flight k cannot be

assigned to the same gate. Note that Equation (10) is binding if and only if flight i and flight k are assigned to gate j (i.e., $x_{ij} = x_{kj} = 1$) because M is an arbitrarily large number.
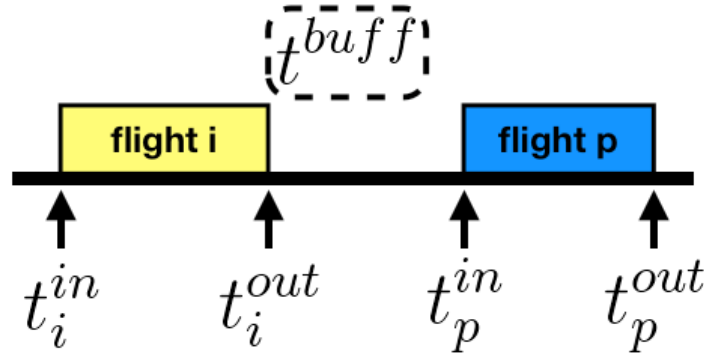
Figure 23: Feasible Gate Schedule with Sufficient Gate Separation.
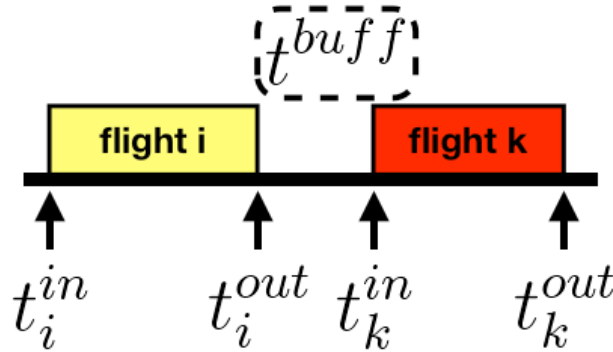
Figure 24: Infeasible Gate Schedule with Insufficient Gate Separation.

3.3 Objective 2: Minimize Aircraft Taxi Time

Recent research on Air Traffic Management (ATM) emphasizes reducing emissions and noise as well as delays. Longer operation times on the airport surface imply more local emissions and noise. In an effort to reduce operational costs and environmental impact, ATM researchers seek to optimize surface operations, among which ramp operations play an important role.

The second objective of the GAP is to minimize the total weighted taxi time in ramp areas. The taxi time depends on the length of the taxi route. However, interfering taxi routes cause taxi delays. If two aircraft taxi in opposite directions on the same taxi lane, one aircraft moves to different taxi lane and it results in taxi delays. Because the taxi route of an aircraft is determined by the locations of its assigned runway and gate, gate assignment is critical to reduce taxi time and taxi delays on ramps. The weighted taxi time in this dissertation consists of weighted nominal taxi time and weighted taxi delays. Nominal taxi time is the sum of unimpeded, i.e. without any taxi delay, taxi time from the arrival spot to the gate and unimpeded taxi time from the gate to the departure spot, which is not necessarily the same as the arrival spot. Spots are the entry/exit points of the ramp area. Nominal taxi time includes the time needed for the aircraft to push back. This study accounts for taxi delays caused by pushback blocking and taxi blocking, which are defined in chapter 2.

As in the case of passenger flow, a link-node map of the ramp area is used for the calculation of nominal taxi times and taxi delays for complex ramp geometry. Figure 25 illustrates a link-node map of a ramp area at Hartsfield-Jackson Atlanta International Airport. The link-node map is applicable to every type of ramp geometry. Different average taxi speeds are applied according to the location of the link. For example, a link connecting a gate node to another node is limited to a low taxi speed and a link connecting two nodes that are not gate nodes is allowed to a higher taxi speed. For each aircraft, the shortest path is calculated from the arrival spot to the gate and from the gate to the departure spot. Nominal taxi time is calculated from the taxi route and average taxi speed of each link on the taxi route. In addition, the arrival time to each node on the route is calculated.
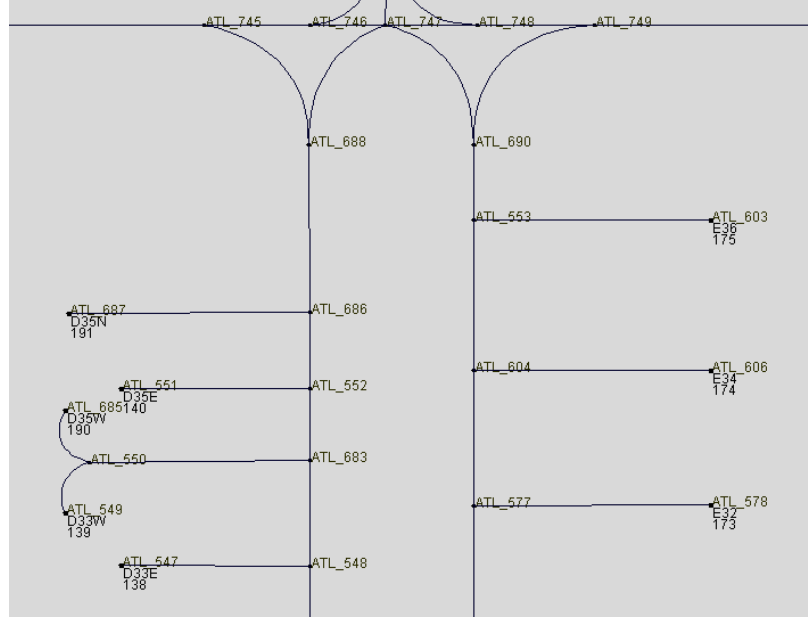
Figure 25: Link-node Map of a Ramp Area at Hartsfield-Jackson Atlanta International Airport.

The nominal taxi time is weighted by the number of passengers on board. Let n_i^{in} denote the number of arrival passengers of flight i and u_j^{in} denote the nominal taxi-in time to gate j. Note that arrival passengers include both destination passengers and transfer passengers from arriving flight i. Then,

$$\text{the weighted taxi-in time of flight } i \text{ is equal to } n_i^{\text{in}} \times u_j^{\text{in}}. \tag{12}$$

Also, let n_i^{out} denote the number of departure passengers of flight i and u_j^{out} denote the nominal taxi-out time from gate j. Note that departure passengers include both origin passengers and transfer passengers to departing flight i. Then,

$$\text{the weighted taxi-out time of flight } i \text{ is equal to } n_i^{\text{out}} \times u_j^{\text{out}}. \tag{13}$$

The weighted nominal taxi time is analogous to the transit time of O&D passengers of objective 1. Similar to the O&D passenger transit time, the weighted nominal taxi time depends on the distance between the gate and entry/exit points. The entry and exit points of O&D passengers are security check points and a baggage claim.

The entry point of aircraft is the arrival spot, and the exit point of aircraft is the departure spot. Arrival and departure spots are determined by runway assignment, which depends on the origin airport of arriving flight and the destination airport of departing flight. When there are multiple spots to the taxiway, the spot closest to the gate and the runway is chosen. Therefore, the weighted nominal taxi time is related to a set of a flight and a gate.

The taxi delay (t^{dly}) is weighted by the total number of passengers on the involved two flights. For instance, if the taxi delay occurs between two arrivals, the total number of passengers is $n_i^{\mathrm{in}} + n_k^{\mathrm{in}}$. In general, the total number of passengers of flights i and k is denoted by $n_i + n_k$, and

$$\text{the weighted taxi delay of flight } i \text{ and flight } k \text{ is equal to } (n_i + n_k) \times t^{\mathrm{dly}}. \quad (14)$$

Taxi delays caused by other events, like the unavailability of gate equipment operators, are not captured in this dissertation. Therefore, a pair of aircraft is always involved in the computation of taxi delays like the calculation of transit time of transfer passengers. In short, the weighted aircraft taxi time can be translated into the total passenger time spent on the ramp.

In summary, there is a taxi delay when any of the following situations occurs:

1. An aircraft occupies a node where other aircraft complete their pushbacks. An extreme example of this issue occurs at Boston Logan International Airport: only one aircraft can taxi through the horseshoe ramp at Boston Logan International Airport, and other aircraft in the horseshoe ramp have to wait until the exit point of the horseshoe ramp is clear. The horseshoe ramp at Boston Logan International Airport is shown in Figure 18.

2. An aircraft taxies through the node occupied by another aircraft in the process of pushing back or in the process of running its checklist after completing its pushback. Examples are illustrated in Figure 20 and Figure 21.

3. Two aircraft taxi on the same link in opposite directions at the same time. Examples are illustrated in Figure 19 and Figure 22.

The formulation of the second objective is given below. The weighted nominal taxi times are expressed by linear terms and the weighted taxi delays are expressed by quadratic terms of decision variables in Equation (15).

$$\text{Obj}_{\text{taxi}} = \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} (n_i^{\text{in}} u_j^{\text{in}} + n_i^{\text{out}} u_j^{\text{out}}) \; x_{ij} + \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} \sum_{k \in \mathcal{F}, k > i} \sum_{l \in \mathcal{G}} (n_i + n_k) t^{\text{dly}} \; x_{ij} \; x_{kl}.$$
(15)

So, the GAP for the second objective is expressed as

Minimize Obj_{taxi} (16)

subject to

$$\sum_{j \in \mathcal{G}} x_{ij} = 1, \; \forall i \in \mathcal{F},$$
(17)

$$(t_i^{\text{out}} - t_k^{\text{in}} + t^{\text{buff}})(t_k^{\text{out}} - t_i^{\text{in}} + t^{\text{buff}}) \le M(2 - x_{ij} - x_{kj}), \; i \ne k, \; \forall i, k \in \mathcal{F}, \; \forall j \in \mathcal{G},$$
(18)

$$x_{ij} \in \{0, 1\}, \; \forall i \in \mathcal{F}, \; \forall j \in \mathcal{G},$$
(19)

where $x_{ij} = \begin{cases} 1 & \text{if flight } i \text{ is assigned to gate } j \\ 0 & \text{otherwise.} \end{cases}$

3.4   Objective 3: Maximize the Robustness of Gate Assignment

The third objective of the GAP is to maximize the robustness of gate assignments. "Robust" means that the gate assignment is resistant to uncertain delays. Indeed, severe delays perturb gate operations by forcing arriving aircraft to wait for gates, or ramp controllers to reassign gates. The disturbances can be reduced if the gate assignment is robust against uncertain delays. Therefore, the objective is to minimize

the (expected) duration of gate conflicts, equivalently. If a gate is still occupied by an aircraft when another aircraft requests the gate, the latter should wait until the assigned gate or another gate is available, which is called a gate conflict. Figure 26 illustrates a gate conflict, where $act_a(i)$ and $act_d(i)$ denote the actual arrival time and the actual departure time of flight i. The gate separation is the time gap between the scheduled departure time of flight i ($sch_d(i)$, red dashed line) and the scheduled arrival time of flight k ($sch_a(k)$, blue dashed line). In Figure 26, flight i is scheduled to leave the gate before flight k arrives, but the departure time of flight i is delayed and flight k arrives earlier than scheduled. So, when flight k arrives, the gate is not released yet and flight k has to wait for $act_d(i) - act_a(k)$.
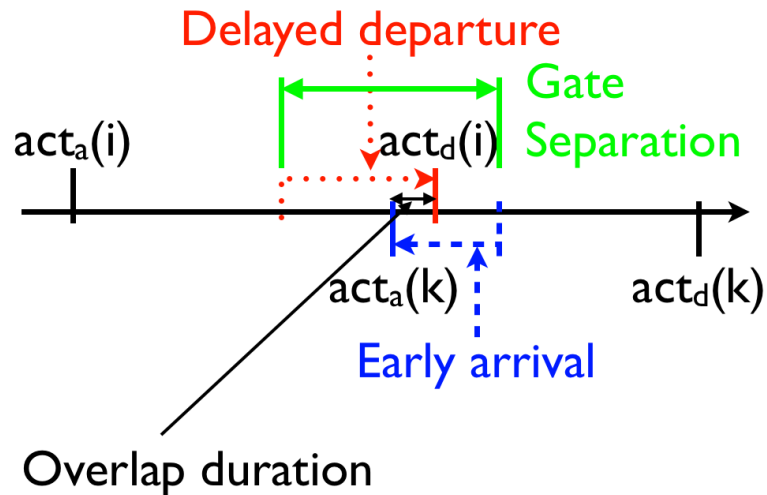
Figure 26: Typical Gate Conflict Where Two Aircraft Need the Same Gate at the Same Time: Flight i is scheduled to depart before flight k arrives at the gate, but the flight k arrives before the flight i pushes back.

Because the actual arrival time and the actual departure time are unknown when gates are assigned, the duration of a gate conflict is estimated based on the probability distributions of arrival delay and departure delay. As shown in chapter 1, arrival delay (dly_a) and departure delay (dly_d) are modeled using a Log-normal distribution. The

actual departure time of flight i and the actual arrival time of flight k are given in Equations (20)-(21), where μ and σ are parameters of the Log-normal distribution and c is the shift parameter.

$$act_d(i) = sch_d(i) + dly_d(i) = sch_d(i) + \{\textbf{Log}-\mathcal{N}(\mu_d, \sigma_d) + c_d\}, \tag{20}$$

$$act_a(k) = sch_a(k) + dly_a(k) = sch_a(k) + \{\textbf{Log}-\mathcal{N}(\mu_a, \sigma_a) + c_a\}. \tag{21}$$

In Figure 26, the duration of gate conflict is $act_d(i) - act_a(k)$. Because the actual times (i.e., $act_d(i)$ and $act_a(k)$) are random variables, the expected duration of gate conflict is calculated below.

$$\text{Expected duration of gate conflict} = \text{E}[act_d(i) - act_a(k), act_d(i) > act_a(k)] \tag{22}$$

$$= \text{E}[sch_d(i) + dly_d(i) - sch_a(k) - dly_a(k), dly_d(i) - dly_a(k) > sch_a(k) - sch_d(i)] \tag{23}$$

$$= \text{E}[\textbf{Log}-\mathcal{N}(\mu_d, \sigma_d) - \textbf{Log}-\mathcal{N}(\mu_a, \sigma_a) - z, \textbf{Log}-\mathcal{N}(\mu_d, \sigma_d) - \textbf{Log}-\mathcal{N}(\mu_a, \sigma_a) > z] \tag{24}$$

$$= \int_0^\infty \int_{y+z}^\infty (x - y - z) f_{dep}(x; \mu_d, \sigma_d, 0) f_{arr}(y; \mu_a, \sigma_a, 0) dx dy, \tag{25}$$

where $z = sch_a(k) - sch_d(i) - c_d + c_a$.

The function f_{dep} is the probability density function (PDF) of departure delays and f_{arr} is the probability density function of arrival delays, which follow Equation (2). Using Equations (20)-(21), Equation (22) is formulated to Equations (23) and (24). It is assumed that the departure delay of flight i and the arrival delay of flight k are independent. So, Equation (24) is calculated by a double integral using the PDFs of departure delays and arrival delays. Equation (25) depends only on z, or equivalently $sch_a(k) - sch_d(i)$, which is the gate separation between flight i and flight k. Because there is no closed form for Equation (25), the double integral is calculated numerically, and Figure 27 shows the expected duration of gate conflict according to gate separations. Note that the expected overlap duration is only about

12 minutes when gate separation is zero. The duration is surprisingly small because early departures and late arrivals occur frequently as shown in Figure 4 and Figure 5.
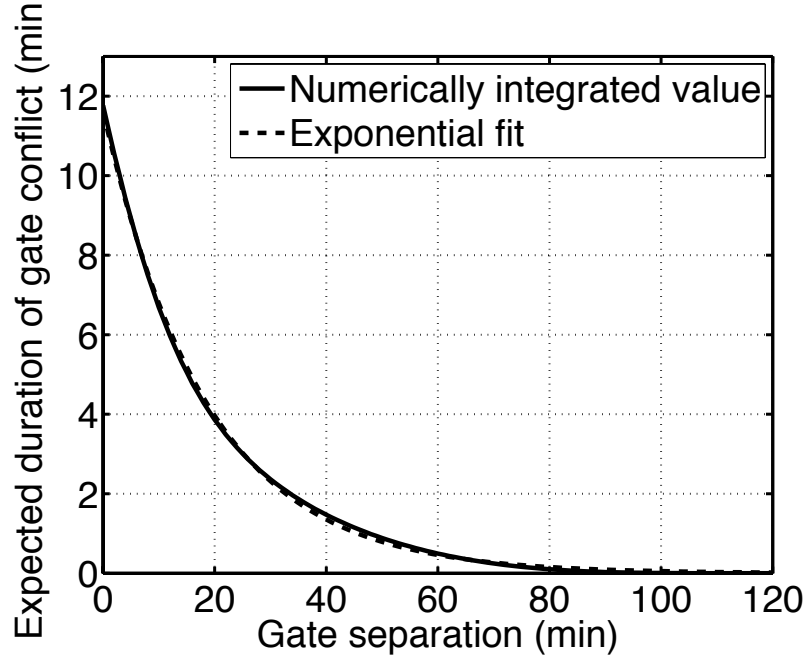
Figure 27: Expected Duration of Gate Conflict as a Function of Planned Gate Separation Between Consecutive Occupancies, Together with the Exponential Fit $11.6 \times 0.95^{\mathrm{sep}(i,k)}$: The expected duration of gate conflict decays exponentially as gate separation increases.

Because the curve decreases exponentially and the calculation of Equation (25) is time-consuming, the curve is fitted to an exponential function given in Equation (26), where $\mathrm{sep}(i, k)$ denotes the gate separation between flight i and flight k. The parameter a is the y-intercept of the exponential function and b is the exponential base. For the NWA data at DTW in March 2006, a and b are 11.63 and 0.9476, respectively. As shown in Figure 27, the exponential function models the expected duration of gate conflict well.

$$\text{Expected duration of gate conflict} \sim a \times b^{\mathrm{sep}(i,k)}. \tag{26}$$

The expected duration of a gate conflict is weighted by the number of arrival passengers (n^{in}) because only arrivals are delayed due to a gate conflict. The formulation

of the third objective is given below. As shown in Equation (26), the expected duration of gate conflict depends on the gate separation. Hence, only if flight i and flight k use the same gate, the expected duration of gate conflict between them contributes to the objective function. In other words, there is no gate conflict between flight i and flight k when their gate assignments are different (i.e., $x_{ij} \, x_{kj} = 0$).

$$\text{Obj}_{\text{robust}} = \sum_{i \in \mathcal{F}} \sum_{k \in \mathcal{F}, k > i} n^{\text{in}} a \times b^{\text{sep}(i,k)} \sum_{j \in \mathcal{G}} x_{ij} \, x_{kj}. \tag{27}$$

The GAP for the third objective is expressed as

Minimize $\text{Obj}_{\text{robust}}$ \hfill (28)

subject to

$$\sum_{j \in \mathcal{G}} x_{ij} = 1, \ \forall i \in \mathcal{F}, \tag{29}$$

$$(t_i^{\text{out}} - t_k^{\text{in}} + t^{\text{buff}})(t_k^{\text{out}} - t_i^{\text{in}} + t^{\text{buff}}) \leq M(2 - x_{ij} - x_{kj}), \ i \neq k, \ \forall i, k \in \mathcal{F}, \ \forall j \in \mathcal{G}, \tag{30}$$

$$x_{ij} \in \{0, 1\}, \ \forall i \in \mathcal{F}, \ \forall j \in \mathcal{G}, \tag{31}$$

where $x_{ij} = \begin{cases} 1 & \text{if flight } i \text{ is assigned to gate } j \\ 0 & \text{otherwise.} \end{cases}$

3.5 Optimization Method for Gate Assignment Problem

The GAP is very difficult to solve with an exact method such as Branch and Bound (B&B). Hence, various heuristics are applied to find a "good" solution within a reasonable amount of time. Among these heuristic algorithms, the Tabu Search (TS) is known to be an effective tool for many combinatorial optimization problems such as the GAP. Xu and Bailey implemented TS for the GAP that minimizes the passenger transit time [67]. Ding et al. suggested an Interval Exchange Move, which generalizes the Exchange Move introduced by Xu and Bailey [67], and an additional move for un-gated flights [25, 26]. They also implemented a greedy method to find a feasible

initial solution. In the remainder of this dissertation, the neighborhood search moves and a greedy method suggested by Ding et al [25, 26] are adopted.

The Genetic Algorithm (GA) is also used to solve the GAP. Gu and Chung introduced the GA for a gate reassignment problem such that the assigned gate number of each flight was analogous to a chromosome [36]. For example, the first gene of a chromosome is the assigned gate number of the first flight. Each chromosome represents a gate assignment. They used one point crossover, which chooses a random crossover point in the parent chromosomes and exchanges the prefix genes of the parent. In the mutation operation, every gene undergoes a random change with a certain probability. Bolat implemented the GA to evenly distribute gate idle times for robust gate assignments [11]. Bolat also implemented the same chromosome structure as Gu and Chung [36]. He mentioned that the chromosome structure can represent an infeasible gate assignment in which two flights use the same gate at the same time (gate conflict). To deal with infeasible gate assignments, he used a strategy to keep only feasible assignments and utilized a strategy based on a mutation operation to repair infeasible ones. Recently, Hu and Di Paolo introduced a uniform crossover operation with a new chromosome structure [42]. Different from one point crossover, uniform crossover basically has multiple crossover points. They grouped flights according to assigned gates and constructed a chromosome with the relative position of a flight in a group. The new chromosome structure can represent queues to gates, but it is not free of the infeasibility. Miao et al. implemented the TS and the GA to solve the truck dock assignment problem, which is very similar to the GAP in terms of minimizing distance [53]. They showed that the TS gives a better solution in a shorter computation time than the GA.

3.5.1 Tabu Search

The TS is a meta-heuristic algorithm introduced by Glover [34]. The TS searches the neighborhood of the current solution using short term memory. At each iteration, feasible neighboring moves are evaluated, and a move that improves objective value is used to find the next solution. In order to escape from local optima, a tabu restriction is applied with short term memory. The tabu restriction prevents the TS from reverting to previous states, but it can be overridden if the candidate move makes the solution better than the current best. Such a rule is called an aspiration criterion. The TS procedure for the GAP is summarized in Table 4.

Table 4: Tabu Search Procedure

Step 1	Generate initial solution, and set the current iteration and all tabu memories to zero.
Step 2	If the current iteration is larger than the maximum iteration, then terminate.
Step 3	Determine a type of neighborhood search moves to apply for the current iteration.
Step 4	Find a set of feasible moves.
Step 5	Evaluate each candidate move.
Step 6	If there exists a move that improves objective value, select it. Otherwise, select the best possible move with the expired tabu memory. (i.e., the corresponding tabu memory is smaller than the current iteration.)
Step 7	Update the tabu memory of the selected move to be randomly larger than the current iteration.
Step 8	Update the current solution and the best objective value (if possible).
Step 9	Increase the current iteration by one, and go back to Step 2.

A greedy algorithm introduced by Ding et al. [25, 26] is used to find an initial solution: it sorts flights in accordance with gate-out times and assigns flights to minimize unoccupied gate time. The maximum iteration is set as $300 \times m - 400$, where m is the number of gates, and the algorithm is terminated if there is no improvement of the objective value after $10 \times m$ iterations past the last best score. Two types of neighborhood search moves are used in step 3. Insert Move shown in Figure 28 switches the assigned gate of an aircraft to another gate. So, Insert Move $(f_a, g_b) \Rightarrow (f_a, g_d)$ is to move a single flight f_a from gate g_b to gate g_d. Prior to evaluating the move $(f_a, g_b) \Rightarrow (f_a, g_d)$, the TS checks whether gate g_d is compatible with flight f_a. For instance, large aircraft cannot access some gates and airlines operate their own gates. Also, the TS neglects the move if a gate separation is shorter than buffer time after the move. Then, the TS evaluates the candidate move. The evaluation of Insert Move is given in the following subsection. Interval Exchange Move shown in Figure 29 swaps the assigned gate of a group of aircraft with that of another group of aircraft. So, Interval Exchange Move $(f_A, g_b) \Leftrightarrow (f_C, g_d)$ is to exchange a set of consecutive flights f_A, which are assigned to g_b, with another set of consecutive flights f_C, which are assigned to g_d. Similarly to Insert Move, compatibilities and gate separations are checked before the TS evaluates the move.
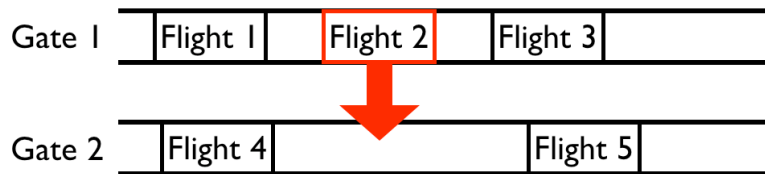
Figure 28: Insert Move: Change a flight's assignment from one gate to another that is also able to serve the equipment type of the flight.
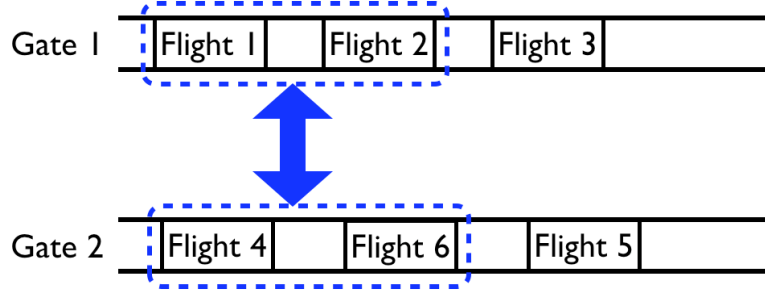
Figure 29: Interval Exchange Move: Swap two groups of assignments if the corresponding two gates are able to serve the equipment types of the groups.

By default, Insert Move is evaluated at every iteration for intensification of the search. However, several conditions override it: If the current iteration is equal to 5, 10, 15, ..., or there is no feasible Insert Move, or the solution is not improved over 50 iterations, then switch to the Interval Exchange Move. These conditions are design parameters and influence the performance of the TS. Insert Move slightly changes the current assignment and searches a narrow neighborhood of the current solution. So, it intensifies a local search. On the other hand, Interval Exchange Move causes relatively large changes in the current assignment. Thus, it helps TS diversify the search. Moreover, keeping the previous set of candidate moves increases the efficiency of TS. Only a small portion of flights is affected after each iteration; hence, the last candidate move set and its evaluation results can be reused in the next iteration. Tabu memories for Insert Move and Interval Exchange Move are chosen uniformly in the intervals [2, 5] min and [3, 7] min.

Our previous experience indicates that the TS can outperform the Branch and Bound and the GA in terms of solution time and solution accuracy for the GAP [47]. This dissertation focuses on the improvement of ramp operations and passengers experience by utilizing the solution of the GAP. Thus, the TS is used to get a good solution for the given problem.

3.5.2 Evaluations of Neighborhood Search Moves

Neighborhood moves are evaluated by means of the difference of objective value. The objective function of the GAP is defined as

$$\text{Obj} = \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} c_{ij}^{\text{lin}}\, x_{ij} + \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{G}} \sum_{k \in \mathcal{F}, k > i} \sum_{l \in \mathcal{G}} c_{ijkl}^{\text{quad}}\, x_{ij}\, x_{kl}. \tag{32}$$

For the first objective, Equation (7), c_{ij}^{lin} is equal to $(n_i^{\text{o}} \frac{d_j^{\text{S}}}{v\text{m}} + n_i^{\text{d}} \frac{d_j^{\text{b}}}{v\text{m}})$, and c_{ijkl}^{quad} is equal to $n_{ik} \frac{d_{jl}}{v\text{m}}$. For the second objective, Equation (15), c_{ij}^{lin} and c_{ijkl}^{quad} correspond to $(n_i^{\text{in}} u_j^{\text{in}} + n_i^{\text{out}} u_j^{\text{out}})$ and $(n_i + n_k)t^{\text{dly}}$, respectively. For the third objective, Equation (27), c_{ij}^{lin} is equal to zero for every i and j, and c_{ijkl}^{quad} is equal to $n^{\text{in}}a \times b^{\text{sep}(i,k)}$ if j is equal to l and zero otherwise. Note that c^{quad}s are symmetric: $c_{ijkl}^{\text{quad}} = c_{klij}^{\text{quad}}$.

If f_a is assigned to g_b, a subset of decision variables is determined: $x_{ab} = 1, x_{aj} = 0$ for $j \neq b$. Hence, the objective function with the assignment (f_a, g_b) is

$$\text{Obj}\,|_{(f_a, g_b)} = c_{ab}^{\text{lin}} + \sum_{i \neq a} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{i \neq a} \sum_j c_{abij}^{\text{quad}} x_{ij}. \tag{33}$$

Similarly, the objective function with the assignment (f_a, g_d) is

$$\text{Obj}\,|_{(f_a, g_d)} = c_{ad}^{\text{lin}} + \sum_{i \neq a} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{i \neq a} \sum_j c_{adij}^{\text{quad}} x_{ij}. \tag{34}$$

Therefore, the evaluation of the Insert Move $(\boldsymbol{f_a, g_b}) \Rightarrow (\boldsymbol{f_a, g_d})$ is

$$\text{Obj}\,|_{(f_a, g_d)} - \text{Obj}\,|_{(f_a, g_b)}$$
$$= \{c_{ad}^{\text{lin}} + \sum_{i \neq a} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{i \neq a} \sum_j c_{adij}^{\text{quad}} x_{ij}\} - \{c_{ab}^{\text{lin}} + \sum_{i \neq a} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{i \neq a} \sum_j c_{abij}^{\text{quad}} x_{ij}\}$$
$$= c_{ad}^{\text{lin}} - c_{ab}^{\text{lin}} + \sum_{i \neq a} \sum_j (c_{adij}^{\text{quad}} - c_{abij}^{\text{quad}}) x_{ij}. \tag{35}$$

Assume that a set of flights f_A are assigned to g_b and another set of flights f_C are

assigned to g_d. Then the objective function with these assignments is

$$\text{Obj} \big|_{(f_A, g_b, f_C, g_d)}$$

$$= \sum_{a \in A} c_{ab}^{\text{lin}} + \sum_{c \in C} c_{cd}^{\text{lin}} + \sum_{i \notin A,C} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{a,a' \in A} c_{aba'b}^{\text{quad}} + \sum_{c,c' \in C} c_{cdc'd}^{\text{quad}} + \sum_{a \in A} \sum_{c \in C} c_{abcd}^{\text{quad}}$$

$$+ \sum_{i \notin A,C} \sum_j (\sum_{a \in A} c_{abij}^{\text{quad}} + \sum_{c \in C} c_{cdij}^{\text{quad}}) x_{ij} + \sum_{i \notin A,C} \sum_j \sum_{k \notin A,C, k>i} \sum_l c_{ijkl}^{\text{quad}} x_{ij} x_{kl}. \qquad (36)$$

Similarly, the objective function with the assignment (f_A, g_d, f_C, g_b) is

$$\text{Obj} \big|_{(f_A, g_d, f_C, g_b)}$$

$$= \sum_{a \in A} c_{ad}^{\text{lin}} + \sum_{c \in C} c_{cb}^{\text{lin}} + \sum_{i \notin A,C} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{a,a' \in A} c_{ada'd}^{\text{quad}} + \sum_{c,c' \in C} c_{cbc'b}^{\text{quad}} + \sum_{a \in A} \sum_{c \in C} c_{adcb}^{\text{quad}}$$

$$+ \sum_{i \notin A,C} \sum_j (\sum_{a \in A} c_{adij}^{\text{quad}} + \sum_{c \in C} c_{cbij}^{\text{quad}}) x_{ij} + \sum_{i \notin A,C} \sum_j \sum_{k \notin A,C, k>i} \sum_l c_{ijkl}^{\text{quad}} x_{ij} x_{kl}. \qquad (37)$$

Finally, the evaluation of the Interval Exchange Move $(f_A, g_b) \Leftrightarrow (f_C, g_d)$ is

$$\text{Obj} \big|_{(f_A, g_d, f_C, g_b)} - \text{Obj} \big|_{(f_A, g_b, f_C, g_d)}$$

$$= \{ \sum_{a \in A} c_{ad}^{\text{lin}} + \sum_{c \in C} c_{cb}^{\text{lin}} + \sum_{i \notin A,C} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{a,a' \in A} c_{ada'd}^{\text{quad}} + \sum_{c,c' \in C} c_{cbc'b}^{\text{quad}} + \sum_{a \in A} \sum_{c \in C} c_{adcb}^{\text{quad}}$$

$$+ \sum_{i \notin A,C} \sum_j (\sum_{a \in A} c_{adij}^{\text{quad}} + \sum_{c \in C} c_{cbij}^{\text{quad}}) x_{ij} + \sum_{i \notin A,C} \sum_j \sum_{k \notin A,C, k>i} \sum_l c_{ijkl}^{\text{quad}} x_{ij} x_{kl} \}$$

$$- \{ \sum_{a \in A} c_{ab}^{\text{lin}} + \sum_{c \in C} c_{cd}^{\text{lin}} + \sum_{i \notin A,C} \sum_j c_{ij}^{\text{lin}} x_{ij} + \sum_{a,a' \in A} c_{aba'b}^{\text{quad}} + \sum_{c,c' \in C} c_{cdc'd}^{\text{quad}} + \sum_{a \in A} \sum_{c \in C} c_{abcd}^{\text{quad}}$$

$$+ \sum_{i \notin A,C} \sum_j (\sum_{a \in A} c_{abij}^{\text{quad}} + \sum_{c \in C} c_{cdij}^{\text{quad}}) x_{ij} + \sum_{i \notin A,C} \sum_j \sum_{k \notin A,C, k>i} \sum_l c_{ijkl}^{\text{quad}} x_{ij} x_{kl} \}$$

$$= \sum_{a \in A} (c_{ad}^{\text{lin}} - c_{ab}^{\text{lin}}) + \sum_{c \in C} (c_{cb}^{\text{lin}} - c_{cd}^{\text{lin}}) + \sum_{a,a' \in A} (c_{ada'd}^{\text{quad}} - c_{aba'b}^{\text{quad}}) + \sum_{c,c' \in C} (c_{cbc'b}^{\text{quad}} - c_{cdc'd}^{\text{quad}})$$

$$+ \sum_{a \in A} \sum_{c \in C} (c_{adcb}^{\text{quad}} - c_{abcd}^{\text{quad}}) + \sum_{i \notin A,C} \sum_j \{ \sum_{a \in A} (c_{adij}^{\text{quad}} - c_{abij}^{\text{quad}}) + \sum_{c \in C} (c_{cbij}^{\text{quad}} - c_{cdij}^{\text{quad}}) \} x_{ij}.$$

$$(38)$$

3.6 Conclusion

This chapter presented three different perspectives of the GAP. Each of them minimizes the total transit time of passengers in an airport, the total taxi time on ramps,

and the total duration of gate conflicts, respectively. The mathematical formulations of the GAP are also given to optimize the three objective functions. All the formulations are constrained to guarantee the feasibility of gate assignments: every flight is assigned to a gate and gate separations are longer than the buffer time. Tabu Search is suggested to get a good solution within a reasonable time. Tabu Search utilizes the Insert Move and the Interval Exchange Move to search the neighborhood of the current solution. The Insert Move changes a flight's gate assignment from one to another, and the Interval Exchange Move swaps the gate assignments of two groups of flights.

CHAPTER IV

TRADE-OFFS AMONG PASSENGERS, AIRCRAFT, AND OPERATIONS

4.1 Introduction

Three objectives of the Gate Assignment Problem (GAP) were presented in the previous chapter. This chapter studies the ways to achieve multiple objectives of the GAP at the same time. First section accounts the trade-off between the first objective, which minimizes the total transit time of passengers, and the second objective, which minimizes the total weighted taxi time on ramps. Next section deals with the trade-off between the first objective and the third objective, which maximizes the robustness of gate assignment. The last section of this chapter presents three metrics for passengers' experience at an airport. Trade-offs among three metrics (or objectives) are analyzed, and a balancing objective function is proposed. Then, the current gate assignment at a major U.S. hub airport is compared to the optimized gate assignment that is based on the balancing objective function.

4.2 Trade-off between Passenger Transit Time and Aircraft Taxi Time

The transit time of passengers is determined by the distance that passengers walk. If an aircraft is assigned to a gate close to the baggage claim, the destination passengers of the aircraft are able to exit the airport in a short time. Suppose that the majority of passengers of a large aircraft transfer to another aircraft at the airport and they are assigned next to each other. Then, the chance of missing flights decreases and the cost for passengers who missed their flights is reduced. On the other hand, the nominal taxi time decreases as the location of a gate is closer to the boundary of the

ramp (i.e., the spot), which is compared with the locations of the baggage claim or security check point that are generally located near the center of passenger terminals. Therefore, it is assumed that there would be a trade-off between passenger transit time and aircraft taxi time.

In this section, the performance index of a gate assignment is defined as the sum of the transit time of passengers in the terminal and the weighted taxi time of aircraft on the ramp area. In other words, the objective function becomes a linear combination of the first objective, Equation (7), and the second objective, Equation (15), of the GAP as shown below.

$$\text{Obj} = (1 - \alpha) \times \text{Obj}_{\text{transit}} + \alpha \times \text{Obj}_{\text{taxi}}. \tag{39}$$

To analyze the trade-off between passenger transit time and aircraft taxi time, a trade-off factor α is defined as a number between 0 and 1. When α is 0, the resulting optimization problem minimizes only the passenger transit time. When α is 1, minimizing the weighted aircraft taxi time is the only objective of the optimization problem.

4.2.1 Numerical Example 1: Parallel Ramps
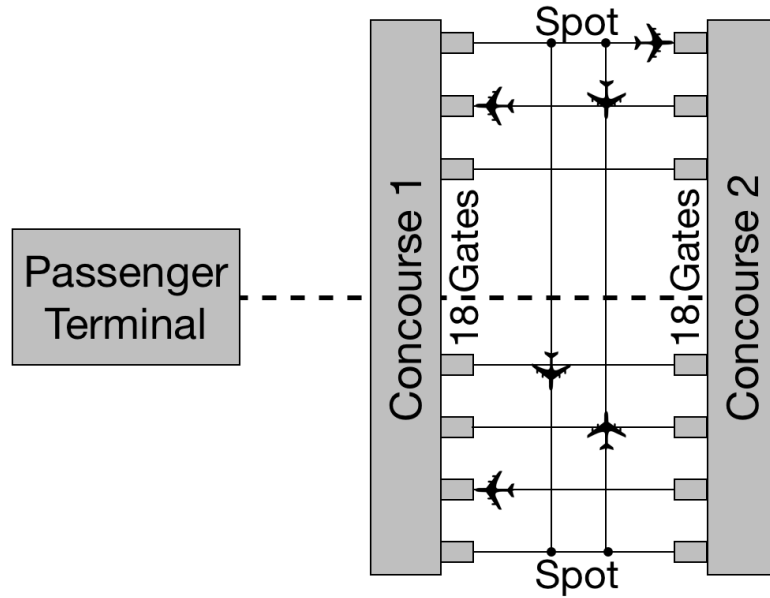
Figure 30: Example 1: Parallel ramp configuration with 36 gates and two parallel taxi lanes.

A parallel ramp configuration is introduced as shown in Figure 30. This configuration resembles Hartsfield-Jackson Atlanta International Airport in overall shape and dimensions though it has only one ramp area. There are two parallel concourses and 18 gates on each concourse. Solid lines represent taxi lanes and dots are located at spots. The underground people mover, which is represented by dashed line, connects the passenger terminal and concourses. The security check point and baggage claim are located in the passenger terminal. The distance between passenger terminal and concourse 1 is 280 meters, which is the same as the distance between two concourses. The inter-gate distance is 35 meters. All the geometries are determined by measuring the satellite image of the Atlanta airport. There are two parallel taxi lanes on the ramp, and they are bi-directional.

Passengers are assumed to walk at a speed of 5 km/h in concourses, and the people mover carries passengers at an average speed of 20 km/h between the passenger terminal and concourses. The assumed passenger walking speed is the average

human walking speed. The Automated People Mover in Hartsfield-Jackson Atlanta International Airport runs one-mile (1.6 km) in five minutes. So, the people mover speed is set to 20 km/h. Average aircraft taxi speed in the ramp area is 12.6 km/h. Balakrishnan and Jung modeled maximum taxi speed as 8 knots (14.8 km/h) in the ramp area [6], so the average taxi speed is set as 85% of the maximum taxi speed. Pushback duration is determined from the ramp operation model in chapter 2.

Two hundred flights are randomly generated. Similar to Xu and Bailey [67], a series of flights arrives in a narrow time window. The whole schedule becomes feasible by limiting the size of each series to be equal to the number of gates. Let f_i be a flight arriving within the r-th series of flights. Then, the arrival time of f_i, t_i^{in}, is randomly chosen within the interval $[90(r\text{-}1)\text{-}10, 90(r\text{-}1)+10]$ minutes. The actual turn around time of each flight is also randomly set within the interval $[40, 60]$ minutes. The parameters related to flights are summarized below.

$$t_i^{\text{in}} = \text{U}(90(r-1)-10, 90(r-1)+10),$$
$$t_i^{\text{out}} = t_i^{\text{in}} + \text{U}(40, 60),$$
$$t^{\text{buff}} = 15 \text{ min}, \tag{40}$$

where f_i is included in the r-th series and $\text{U}(a, b)$ is a uniform random variable in $[a, b]$. Because there are 36 gates and each series of flights consists of 36 flights, the number of series is 6. So, the entire flights are scheduled in 9-hour window.

Passenger flow data are generated as follows: The number of O&D passengers is generated within the interval $[10, 60]$. It is assumed that most transfer passengers do not choose connecting flights whose departure times are too close or too far from the arrival times of the previous flight legs. If $t_k^{\text{out}} - t_i^{\text{in}}$ is in the interval $[30, 120]$ minutes, transfer passengers are generated randomly between the interval $[0, 10]$.

These parameters are given below.

$$n_i^{\mathrm{o}} = \mathrm{U}(10, 60),$$

$$n_i^{\mathrm{d}} = \mathrm{U}(10, 60),$$

$$n_{ik} = \mathrm{U}(0, 10), \text{ if } t_i^{\mathrm{in}} + 30 \leq t_k^{\mathrm{out}} \leq t_i^{\mathrm{in}} + 120 \text{ or } t_k^{\mathrm{in}} + 30 \leq t_i^{\mathrm{out}} \leq t_k^{\mathrm{in}} + 120.$$

$$(41)$$

Using the ramp configuration, flight schedules, and passenger data, the objective function shown in Equation (39) is solved with the constraints given by Equations (9)-(11). The trade-off factor α increases from 0 to 1 with a step size of 0.1.
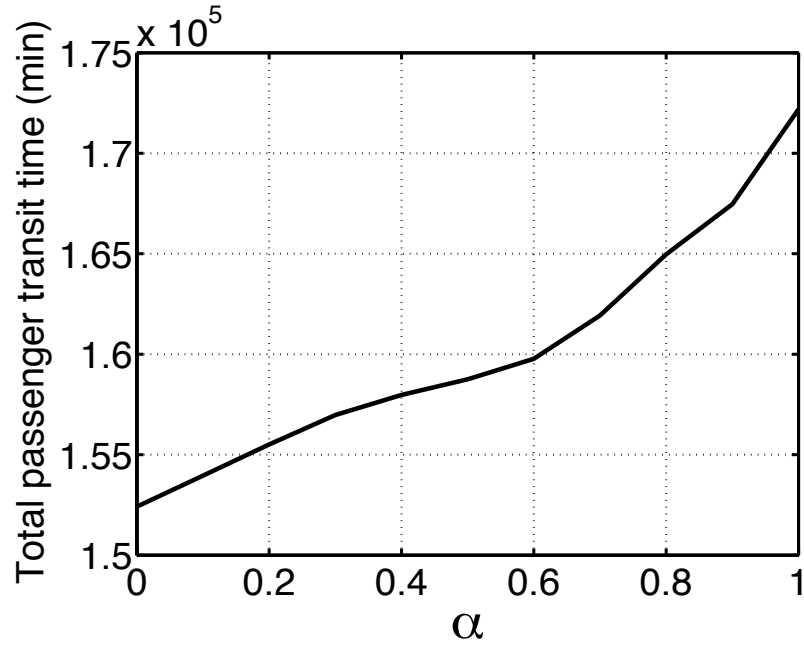
Figure 31: Example 1: α versus total transit time.
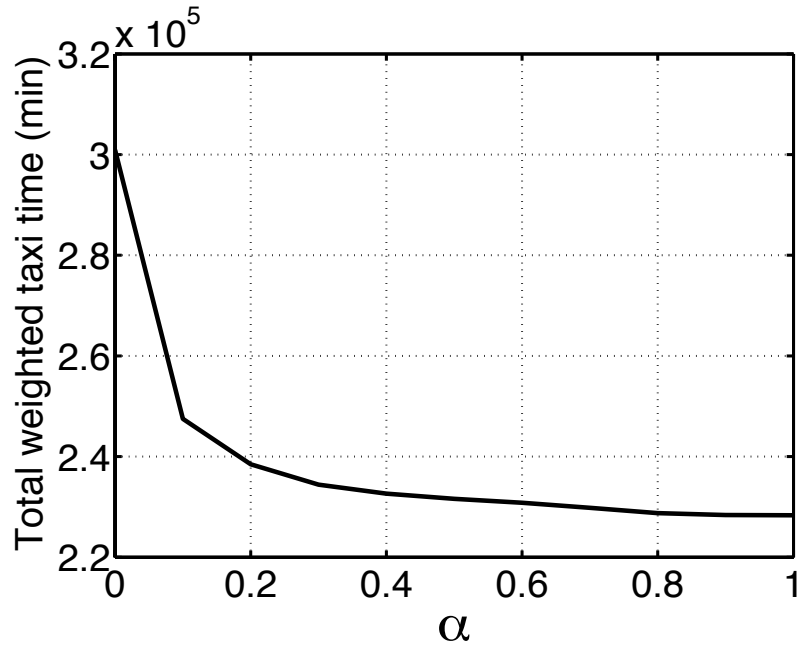
Figure 32: Example 1: α versus total weighted taxi time.
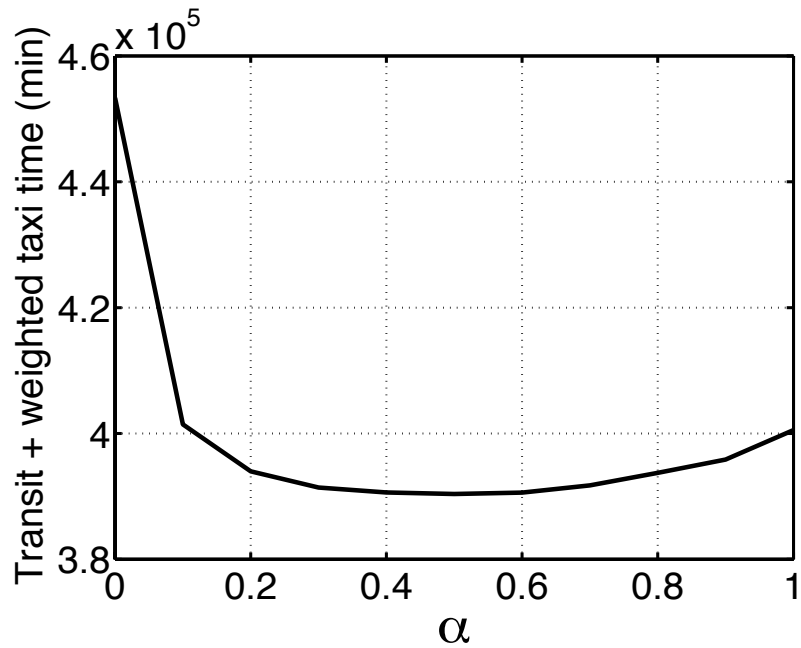
Figure 33: Example 1: Sum of transit time and weighted taxi time.

Total passenger transit time and total weighted aircraft taxi time are shown in Figure 31 and Figure 32. As α increases, total passenger transit time increases.

Specifically, passenger transit time increases by 13% when α varies from 0 to 1. At the same time, total weighted aircraft taxi time decreases when α increases from 0 to 1. When α is 1, weighted aircraft taxi time is 24% shorter than when α is 0. Hence, total weighted aircraft taxi time is more sensitive to α than total passenger transit time.

Figure 33 shows the sum of total transit time and total weighted taxi time. As predicted, there is a trade-off between passenger transit time and aircraft taxi time. In the region of [0.4 0.6] of α, the sum of total transit time and total weighted taxi time is minimal, which means the gate assignment balances land-side congestion and air-side congestion. More specifically, the sum is minimal when α is 0.5. However, policy makers, e.g., airlines, ramp tower, etc., may consider changing the value of the "cost index" α according to their policies and priorities.

4.2.2   Numerical Example 2: Horseshoe Ramps
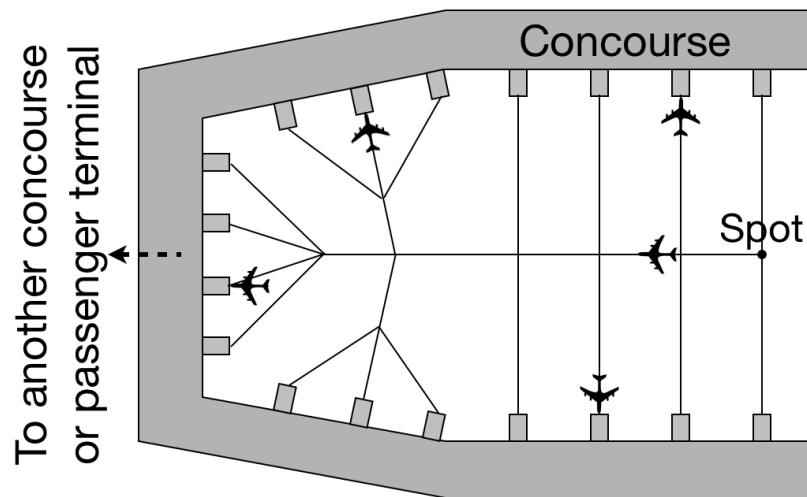
Figure 34: Example 2: Horseshoe configuration.

Another example shown in Figure 34 resembles the horseshoe ramp of Boston Logan International Airport. Example 2 consists of two horseshoe ramps and a passenger

terminal. Similar to example 1, the underground people mover connects the pas-
senger terminal and concourses. Each horseshoe ramp has 18 gates and there is an
underground people mover's stop in the middle of each concourse. The radius of the
rounded part is 100 meters and inter-gate distance is 35 meters. In the horseshoe
configuration, there is only one spot on a ramp, and some gates share a pushback
route. Thus, while an aircraft pushes back from the center gate, the adjacent gates
are inaccessible. Also, while an aircraft enters the ramp through the spot, no other
aircraft can taxi in or out of the ramp. In this example, such blockages are assumed,
for simplicity, to cause a fixed length of taxi delay. Despite this assumption, the
proposed optimization problem can capture potential or predicted congestion on the
ramp. The same flight schedules and passenger data of example 1 are used again for
example 2.
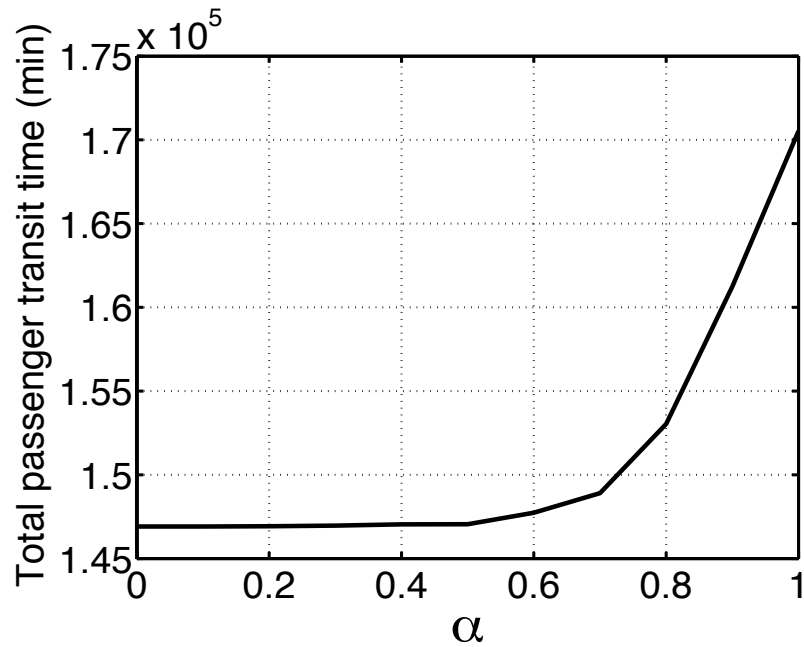
Figure 35: Example 2: α versus total transit time.
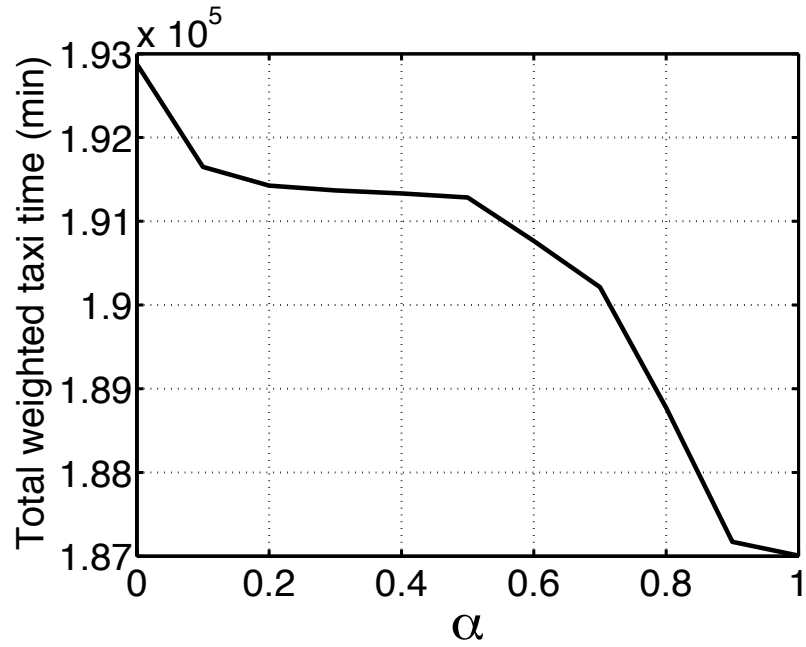
Figure 36: Example 2: α versus total weighted taxi time.
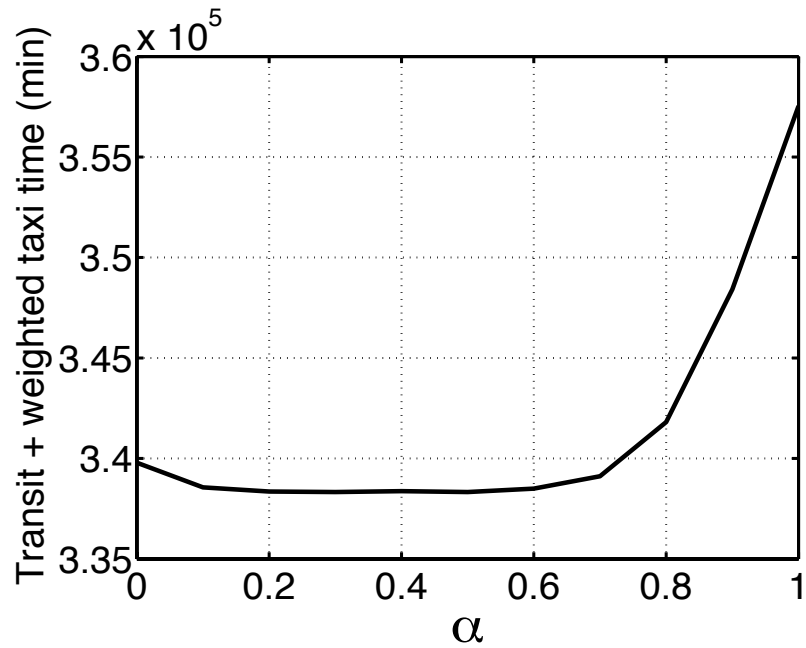
Figure 37: Example 2: Sum of transit time and weighted taxi time.

A trade-off between passenger flow and ramp congestion is shown in Figure 35 and Figure 36. Total passenger transit time does not increase much until α becomes 0.5.

However, total weighted taxi time shows some steep changes of slope when α is 0.1, 0.5 and 0.7. Specifically, total weighted taxi time does not change much while α is in the interval [0.2, 0.5]. Therefore, the sum of total transit time and total weighted taxi time remains the same while α is in the interval [0.2, 0.5] as shown in Figure 37. That is, total transit time and total weighted taxi time are well-balanced in that interval.

4.3 Trade-off between Passenger Transit Time and Robustness of Gate Assignment

The previous section presented the trade-off between passenger transit time and aircraft taxi time and suggested a way balancing these two objectives of the GAP. This section analyzes the trade-off between passenger transit time and the robustness of gate assignment. The third objective, Equation (27) of the GAP tends to distribute flight schedules over gates in order to disperse gate separations. As a consequence, connecting flights are also likely to be scattered over gates and passenger transit time tends to increase. In order to analyze the trade-off, the objective function is given as a linear combination of the first objective, Equation (7), and the third objective, Equation (27), of the GAP as shown below.

$$\text{Obj} = (1 - \alpha) \times \text{Obj}_{\text{transit}} + \alpha \times \text{Obj}_{\text{robust}}. \tag{42}$$

Similarly, a trade-off factor α is introduced. When α is 0, the resulting optimization problem minimizes only the passenger transit time. When α is 1, minimizing the duration of gate conflicts is the only objective of the optimization problem. Two ramp configurations, flight schedules, and passenger data of the previous section are used again in this section.

4.3.1 Numerical Example 1: Parallel Ramps
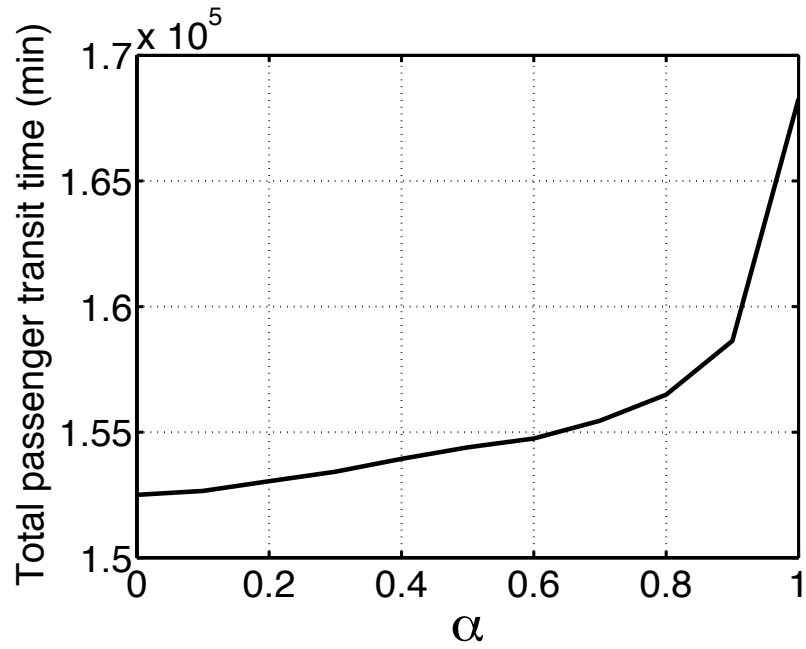
Figure 38: Example 1: α versus total transit time.
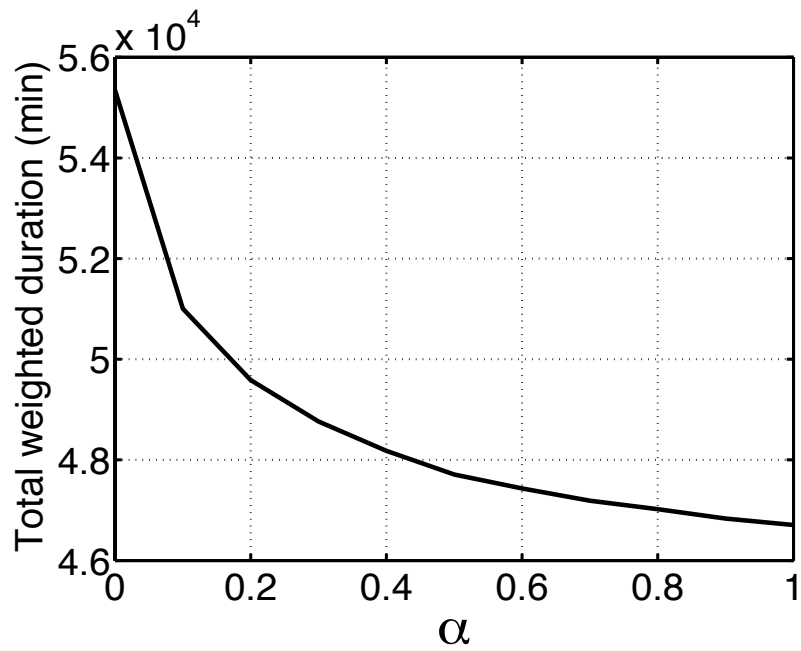
Figure 39: Example 1: α versus total weighted gate conflict duration.
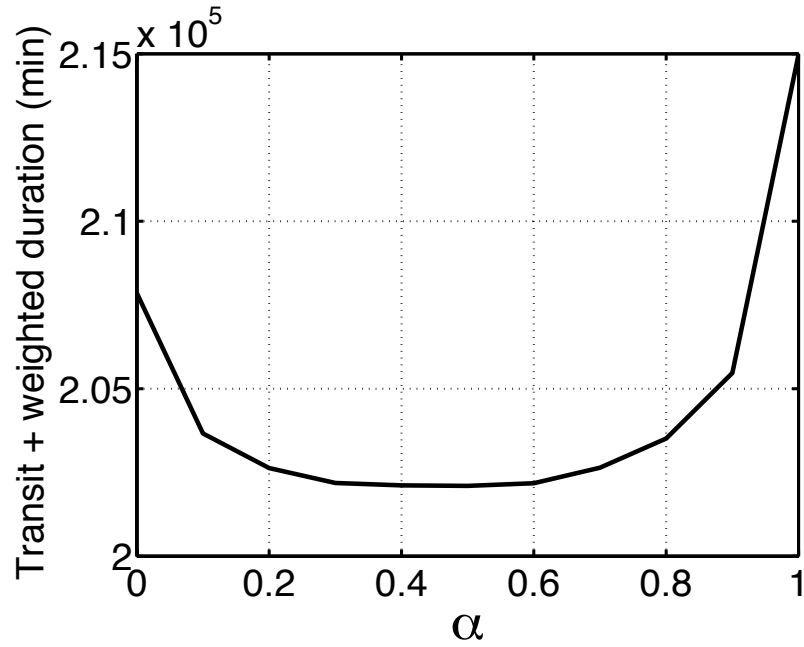
Figure 40: Example 1: Sum of transit time and weighted gate conflict duration.

Figure 38 and Figure 39 illustrate changes of passenger transit time and weighted gate conflict duration according to the trade-off factor α. As α increases, passenger transit time increases and weighted gate conflict duration decreases. Note that the order of magnitude of passenger transit time is larger than that of weighted gate conflict duration because the duration of gate conflicts is less than few minutes in general as shown in Figure 27. The sum of passenger transit time and weighted gate conflict duration is shown in Figure 40. The sum is minimal when α is in the interval [0.4, 0.5].

4.3.2 Numerical Example 2: Horseshoe Ramps
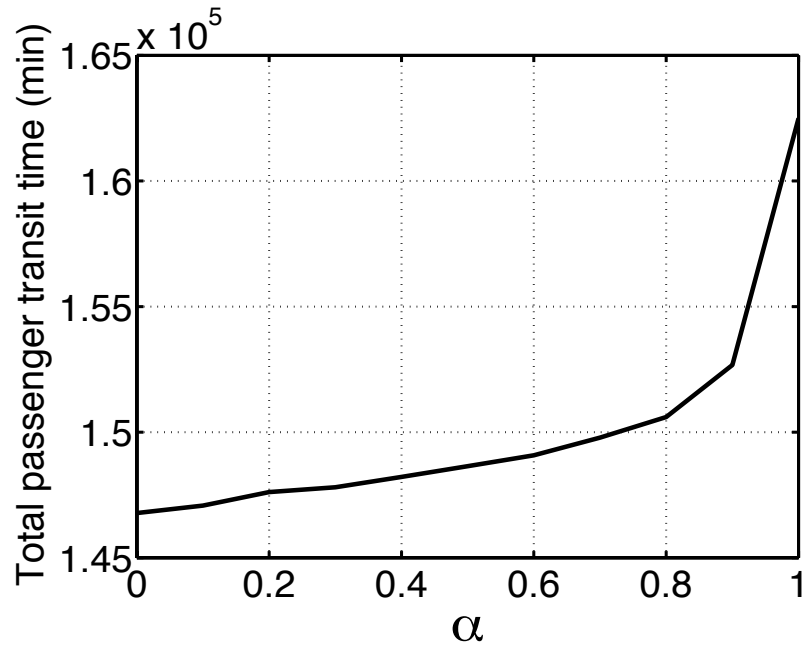
Figure 41: Example 2: α versus total transit time.
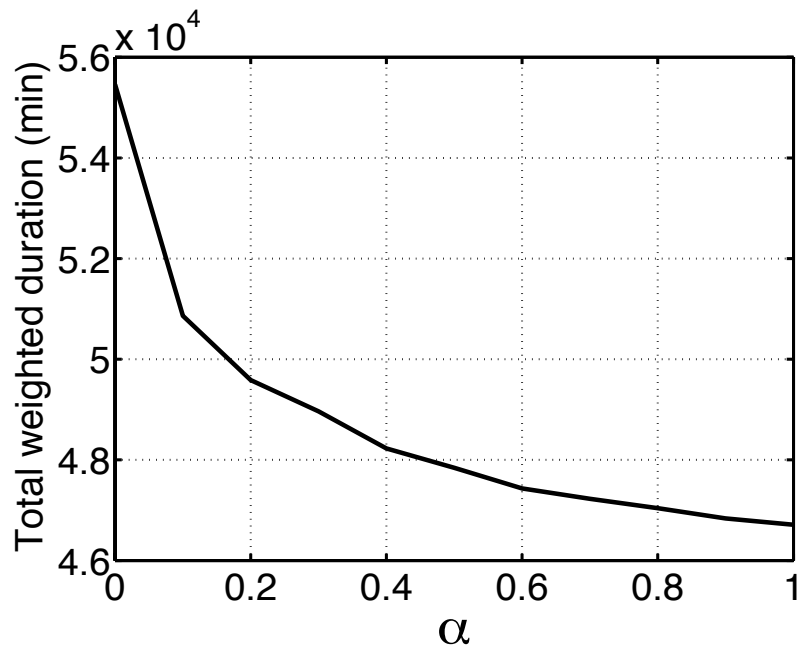
Figure 42: Example 2: α versus total weighted gate conflict duration.
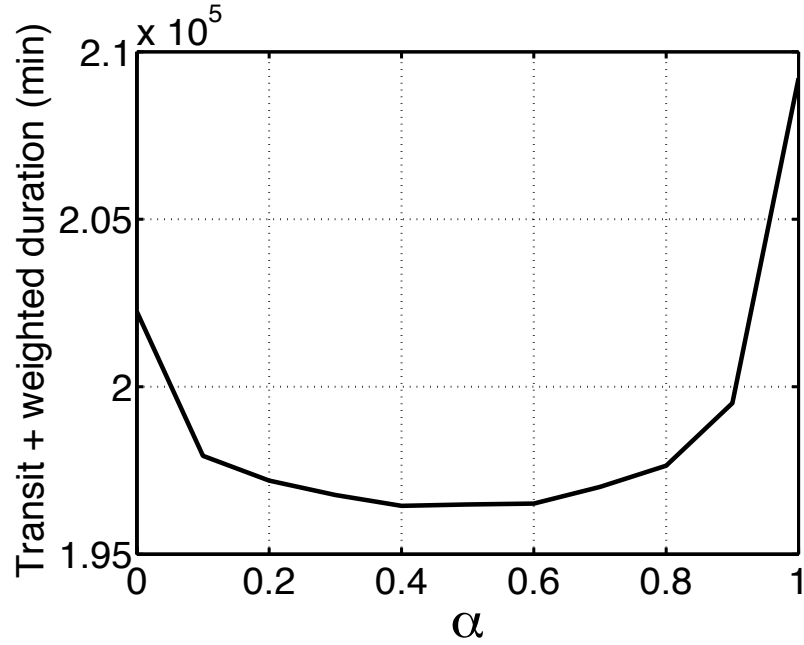
Figure 43: Example 2: Sum of transit time and weighted gate conflict duration.

Passenger transit time, weighted gate conflict duration, and the sum of them are illustrated in Figures 41-43. They are similar to the example 1. In this case, the sum is minimal when α is equal to 0.4. From two examples, it is concluded that the objective 3 of the GAP reduces gate conflicts but increases passenger transit time, and there is a trade-off between the robustness of gate assignment and passenger transit time.

4.4 Passengers' Experience at an Airport

The performance of an air transportation system has been assessed with flight-based metrics, e.g., flight delays. However, the flight-based metrics do not necessarily capture passengers' delays during their full itineraries, especially in hub-and-spoke networks. Cook et al. proposed new passenger-oriented performance metrics that count the number of missed connections and cancelled flights as well as flight delays [23]. Using the passenger-oriented metrics, they tried to reflect passengers' experiences

during their trips. In particular, major hub airports such as Hartsfield-Jackson Atlanta International Airport have a significant impact on the performance of the entire network, and transfer passengers in such hub airports may represent the largest share of traffic and are most vulnerable to delays that can severely perturb their journeys. It is possible that a single delay "snowballs" through the entire air traffic network [1]. The cost of congestion and delays in an air transportation system is huge. According to Airlines for America, direct aircraft operating cost of delays was about $7.7 billion in 2011 [3]. Also, a delayed aircraft cost an additional $39 per hour for extra gates, ground personnel, and airline customers' costs.

Passengers' experience is becoming a key metric to evaluate the air transportation system's performance. Efficient and robust tools to handle airport operations are needed along with a better understanding of passengers' interests and concerns. This section is concerned with airport gate scheduling for improved passenger experience while ensuring robust air-side operations. Trade-offs among three metrics accounting for passengers, aircraft, and operations are analyzed, and a balancing objective function is proposed.

Most air travelers have experienced walking long distances in a passenger terminal to catch a flight or waiting on board their aircraft while it is waiting for a gate or is delayed by the movement of another aircraft. Many such situations can be resolved or reduced by proper gate scheduling or assignment.

The first metric for passengers' experience is the transit time of passengers in a passenger terminal, which is the first objective of the GAP, Equation (7) in chapter 3. This is the most common objective of traditional studies focusing on gate assignment. The second metric for passengers' experience is the taxi time on ramps, which is the second objective of the GAP, Equation (15). The second metric represents the time spent on the ramp by passengers. The last metric for passengers' experience is the robustness of gate assignment, which is the third objective of the GAP, Equation (27).

The last metric represents the time waiting for a gate after landing.

All three metrics cannot be optimized at the same time. Hence, this section presents trade-offs among metrics using flight schedules at a U.S. major hub airport.

4.4.1 Data Source

Prior studies on gate assignment rely on fictitious passenger data (e.g., number of transfer passengers), because such data are not published. Thanks to a major U.S. carrier, this study is able to assign airport gates and analyze gate assignments with the actual number of transfer passengers at a U.S. major hub airport. The carrier provided flight schedules and transfer passenger data from May 1st, 2011 at the hub airport. Because the only available data are the number of transfer passengers of the carrier, all the flights are assumed to be full with passengers, and passengers other than those transferring within the carriers flights are considered to be origin and destination (O&D) passengers.

4.4.2 Trade-offs Among Metrics for Passengers' Experience

It was shown in previous sections that there are trade-offs between objectives of the GAP. In order to analyze the trade-offs among the three metrics, a composite objective function is given below.

$$\text{Obj} = w_{\text{transit}}\text{Obj}_{\text{transit}} + w_{\text{taxi}}\text{Obj}_{\text{taxi}} + w_{\text{robust}}\text{Obj}_{\text{robust}}, \tag{43}$$

$$\text{where } w_{\text{transit}} + w_{\text{taxi}} + w_{\text{robust}} = 1. \tag{44}$$

The composite objective function is a linear combination of Equation (7), Equation (15), and Equation (27). The quantities w_{transit}, w_{taxi}, and w_{robust} are the weighting factors of the metrics. For instance, when w_{transit} is 1, the resulting optimization problem minimizes passenger transit time only. In the trade-off study that follows, the weighting factors are explored in increments of 0.1, so the number of possible combinations of the weighting factors is 66. All the possible combinations are evaluated

for the analysis of trade-offs of multiple metrics.
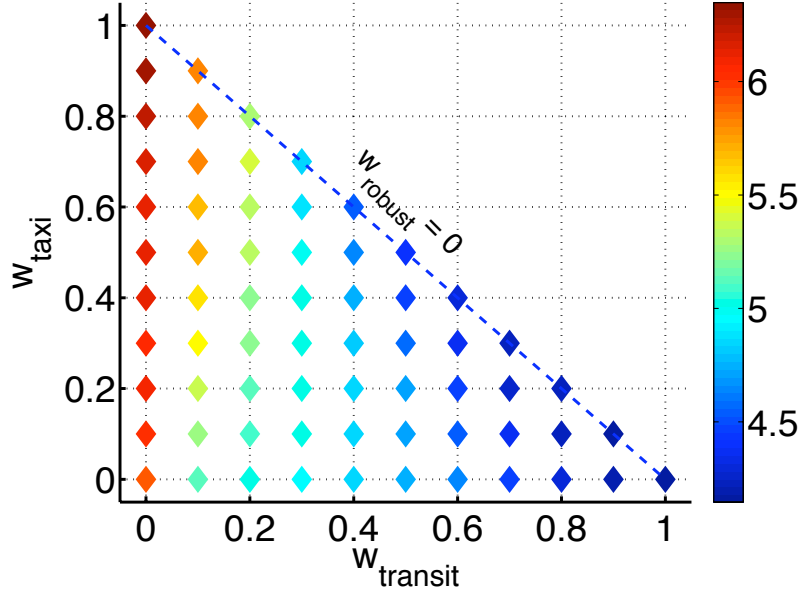
Figure 44: Average Transit Time in Minutes per Passenger for 66 Values of $(w_{transit}, w_{taxi}, w_{robust})$: Transit times are color-coded from blue (~ 4 min) to red (~ 6.5 min).

Figure 44 illustrates the average transit time experienced by each passenger, which is given in Equation (45).

$$\text{Average Transit Time} = \frac{\text{Obj}_{transit}}{\text{Number of Passengers}}. \tag{45}$$

The number of passengers is the sum of the number of O&D passengers and the number of transfer passengers. Each data point of Figure 44 represents a value of three weighting factors $(w_{transit}, w_{taxi}, w_{robust})$. The value of the horizontal axis is $w_{transit}$ and the value of the vertical axis is w_{taxi}. The quantity w_{robust} is obtained from Equation (44) because the sum of three weighting factors is equal to 1. For instance, the bottom-left vertex corresponds to the value $(w_{transit}, w_{taxi}, w_{robust}) = (0, 0, 1)$. The passenger transit time for each value of the weighting factors is color-coded: the blue-end indicates the shortest transit time and the red-end indicates the longest transit time. As expected, the average transit time experienced by each

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passenger tends to become shorter as $w_{transit}$ gets larger, and the minimal transit time corresponds to $w_{transit} = 1$.
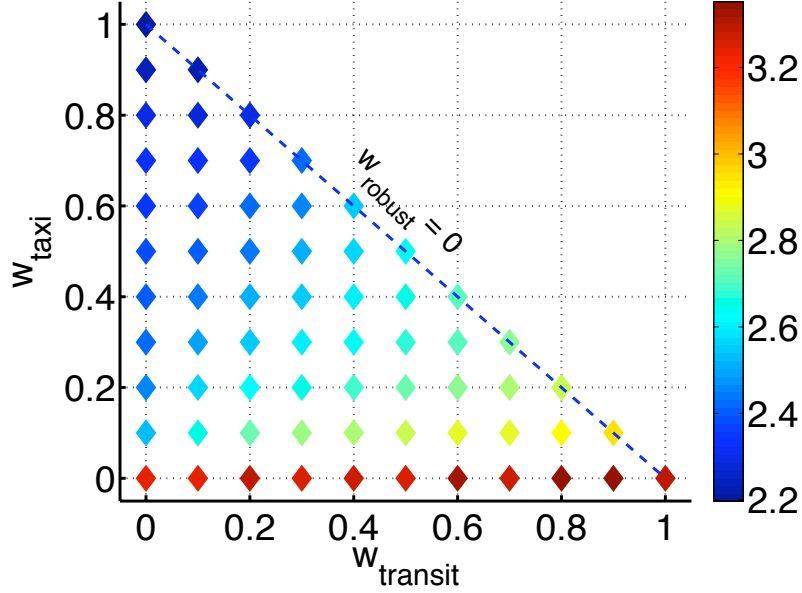
Figure 45: Average Taxi Time in Minutes per Passenger for 66 Values of $(w_{transit}, w_{taxi}, w_{robust})$: Taxi times are color-coded from blue (~ 2.2 min) to red (~ 3.4 min).

Figure 45 shows the average taxi time experienced by each passenger, which is given in Equation (46).

$$\text{Average Taxi Time} = \frac{\text{Obj}_{taxi}}{\text{Number of Passengers on Board}}. \tag{46}$$

Note that the number of passengers on board is not equal to the number of passengers. Transfer passengers take flights twice (an arrival and a departure), so they count twice. Hence, the number of passengers on board is larger then the number of passengers. Each data point represents a value of the weighting factors the same as Figure 44. Similar to Figure 44, the average taxi time tends to become shorter as w_{taxi} gets larger, and the minimal taxi time corresponds to $w_{taxi} = 1$.

From Figure 44 and Figure 45, the trade-off between average transit time and average taxi time per passenger can be analyzed. First, w_{robust} is set to zero, which

corresponds to $w_{transit}$ and w_{taxi} standing on the longest edge of the triangular shape. Then, there are 11 data points on the line from $(0, 1, 0)$ to $(1, 0, 0)$. When $w_{transit}$ is 0 and w_{taxi} is 1, the average transit time is the longest and the average taxi time is the shortest along the line ($w_{robust} = 0$). On the other hand, when $w_{transit}$ is 1 and w_{taxi} is 0, the average transit time is the shortest and the average taxi time is the longest along the line ($w_{robust} = 0$). Table 5 shows the details on the trade-off between average transit time and average taxi time per passenger when w_{robust} is equal to zero. Focusing on one metric alone will harm the others.

Table 5: Trade-off Between Average Transit Time and Average Taxi Time When $w_{robust} = 0$

$(w_{transit}, w_{taxi}, w_{robust})$	Average Transit Time	Average Taxi Time
$(0, 1, 0)$	6.3 min	2.2 min
$(1, 0, 0)$	4.1 min	3.3 min
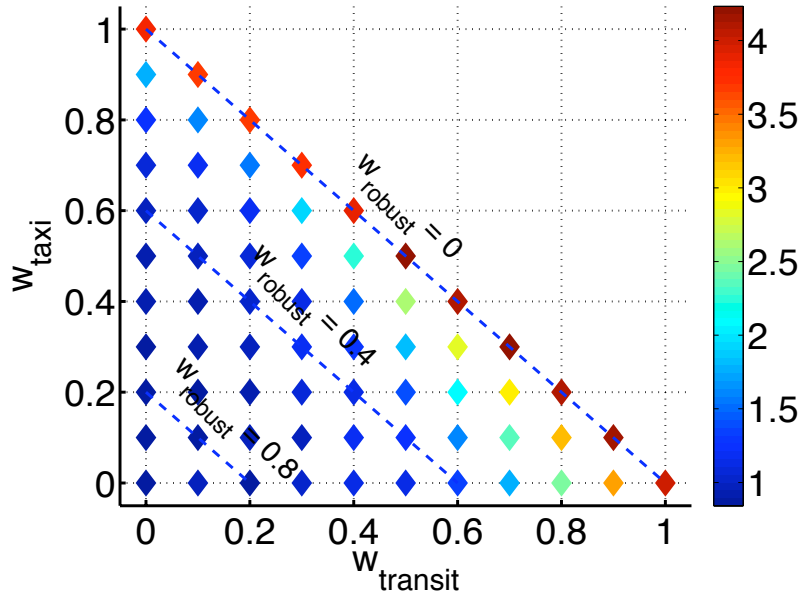
Figure 46: Average Duration of Gate Conflict in Minutes per Passenger for 66 Values of $(w_{transit}, w_{taxi}, w_{robust})$: Gate conflict durations are color-coded from blue (~ 1 min) to red (~ 4 min).

Figure 46 shows the average gate conflict duration experienced by each passenger, which is given in Equation (47).

$$\text{Average Gate Conflict Duration} = \frac{\text{Obj}_{\text{robust}}}{\text{Number of Arrival Passengers}}. \quad (47)$$

Note that the arrival passengers are the passengers who take flights arriving the airport. Similar to the previous analyses on transit time and taxi time, the duration of gate conflict becomes shorter as w_{robust} gets larger, and the minimal duration of gate conflict corresponds to $w_{\text{robust}} = 1$.

From Figures 44-46, it is concluded that we are not able to minimize all the metrics at the same time: transit time is minimal at $(w_{\text{transit}}, w_{\text{taxi}}, w_{\text{robust}}) = (1, 0, 0)$, taxi time is minimal at $(w_{\text{transit}}, w_{\text{taxi}}, w_{\text{robust}}) = (0, 1, 0)$, and gate conflict duration is minimal at $(w_{\text{transit}}, w_{\text{taxi}}, w_{\text{robust}}) = (0, 0, 1)$. Hence, decision makers such as airlines and air navigation service providers need to select a gate assignment scheme based on their policy and preferences.

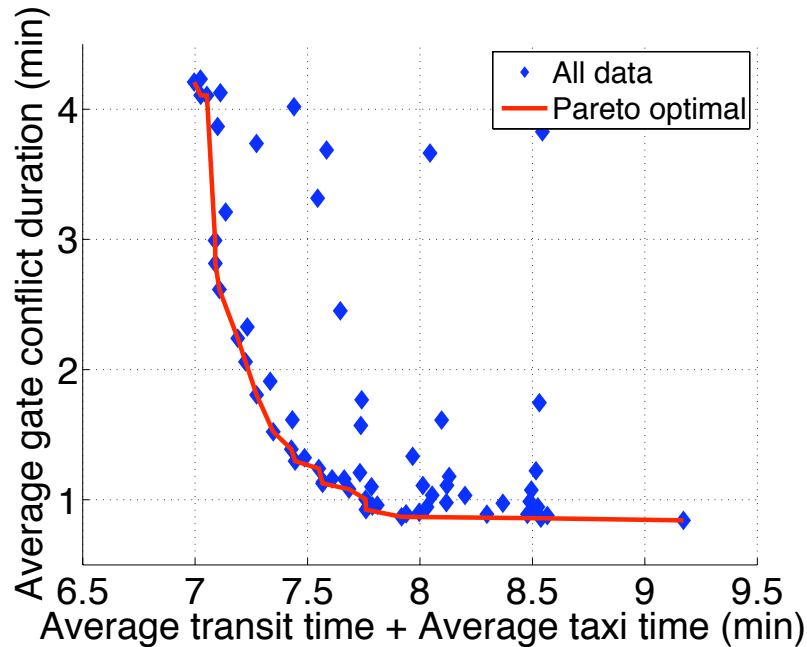**Figure 47:** Average Movement Time and Average Waiting Time for 66 Values of $(w_{\text{transit}}, w_{\text{taxi}}, w_{\text{robust}})$: There is a trade-off between movement time and waiting time.

Figure 47 shows average movement time and average waiting time. The average

movement time is the sum of the average transit time shown in Figure 44 and the average taxi time shown in Figure 45, and the average waiting time is the average duration of gate conflict shown in Figure 46. Hence, the average movement time is the time for a passenger to certainly spend in the passenger terminal and on the ramp area, and the waiting time is uncertain to spend. Therefore, Figure 47 shows a trade-off between certain time and uncertain time spent in the passenger terminal and ramp area, which is indicated by the pareto frontiers. When the certain movement time decreases, passengers are more likely to wait on board for a gate after landing. On the other hand, when the expected waiting time is reduced, passengers certainly spend more time in the passenger terminal and the ramp area.

4.4.3 Comparison Between the Current Gate Assignment and the Optimized Gate Assignment

Then, an optimized gate assignment is compared to the current gate assignment in order to assess how airlines accommodate passengers' experience in the three metrics proposed in this dissertation. The current gate assignment is obtained from the carrier, and the optimized gate assignment is chosen with $(\mathrm{w_{transit}, w_{taxi}, w_{robust}}) = (0.2, 0.2, 0.6)$. However, the choice of the weighting factors can depend on the policy of airport gate managers and airlines. Figure 48 shows the comparison of the current gate assignment and the optimized gate assignment. From the perspective of a passenger, the average taxi time is the time spent on the ramp and the average duration of gate conflict is the time waiting for a gate, which happens only to arrivals. It is shown that the optimized gate assignment can improve all the metrics compared to the current gate assignment. Specifically, average transit time, average taxi time, and average gate conflict duration are reduced by 6%, 18%, and 81% respectively with the optimized gate assignment. In conclusion, the saving from the optimized gate assignment is 4.7 minutes per passenger, which means that passengers save 4.7 minutes on average in the passenger terminal and the ramp area.
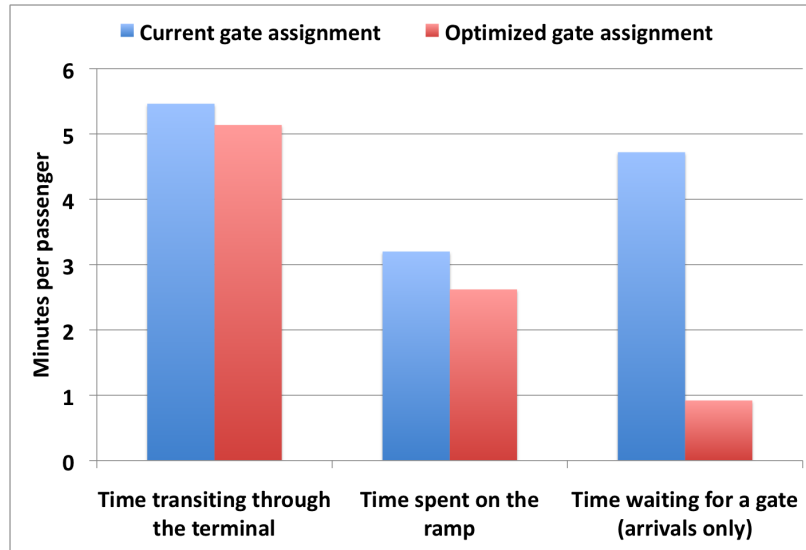
Figure 48: Comparison of the Current Gate Assignment and the Optimized Gate Assignment: The current gate assignment is obtained from the U.S. carrier and the optimized gate assignment corresponds to $(w_{transit}, w_{taxi}, w_{robust}) = (0.2, 0.2, 0.6)$.

4.5 Conclusion

This chapter presented three of the metrics that most affect passengers' experience at congested airport. These metrics are transit time of passengers in passenger terminals; aircraft taxi time on ramps; and the duration of gate conflicts. It was shown that these metrics compete against each other, so an objective function that balances three metrics is proposed. The objective function can simulate the preferences of the airline, the air navigation service provider, or passengers by combining a value of the weighting factors. Different values of the weighting factors result in significantly different gate allocation strategies. Moreover, the performance obtained by optimizing the balanced objective function appears to outperform the observed, real-life gate assignment in every metric. Therefore, and although further studies are necessary to understand this difference in performance, the gate assignment of the airport offers the potential to improve the efficiency of traffic flow in passenger terminals and on ramps, as well as the robustness of gate operations.

CHAPTER V

GATE ASSIGNMENT AND DEPARTURE METERING

5.1 Introduction

Departure metering (or gate holding) is an approach to reduce taxi delays and emissions in the departure process, while maintaining airport departure throughput (take-off rate), which is motivated by the fact that the number of take-offs per minute is saturated when the number of aircraft that taxi out (denoted N) is greater than a saturation point (N^*) [61, 59, 4]. Departure metering is equivalent to freeway ramp-metering control in the ground transportation literature [49, 57]. Shumsky, in his dissertation [61], noticed that the take-off rate rises with N and levels off at a certain value after N exceeds N^*. As a result, the take-off rate corresponding to N^* and above represents the airport's departure capacity. Departure metering manages to keep N near N^* by controlling pushback clearances, and the first analytic assessment of the departure metering was conducted by Pujet et al. [59]. When N exceeds N^* or N^{ctrl} (control point), departure metering becomes active and aircraft requesting pushback clearance are held at gates. Independent studies [8, 45, 12, 56, 37] confirm that taxi delays in the departure process are transformed to gate-holding delays by utilizing departure metering, without sacrificing airport capacity. Departure metering was implemented experimentally at Boston Logan International Airport following the development of suitable human interfaces [63], 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 [16], has been field-tested at Paris Charles de Gaulle Airport in early 2013 as part of the Dflex program [2]. The results were encouraging enough that Dflex has remained active since then. One issue is whether this 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 La Guardia Airport (LGA), John F. Kennedy Airport (JFK), or Hartsfield-Jackson Atlanta International Airport (ATL). Recent studies relating to departure metering by Jung et al. [45] and Simaiakis et al. [63] indicate that the research community is still concerned with consequences of departure metering on terminal air-side congestion. At the same time, the rapid move of departure metering techniques towards implementation in Europe, in the U.S., and 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 chapter 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 is called 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 pushback, or the arriving aircraft must wait for the gate hold to terminate. In both situations, departure metering is prevented from working to its full potential. This study sheds light on the importance of understanding the impact of gate assignment on departure metering and vice-versa.

In order to simulate the airport departure process, a queuing model is introduced. The model is calibrated and validated with actual data from LGA and a major U.S. hub airport. Then, the model simulates the airport departure process with the current

gate assignment and a smart gate assignment to assess the impact of gate assignment on departure metering.

5.2 Airport Departure Model of La Guardia Airport

5.2.1 Queuing Model

Many researchers use a queuing model for simulating metered airport departure processes [59, 62, 15, 17]. The queuing models have a similar structure: When an aircraft is ready for pushback, it enters a pushback queue. When departure metering is inactive, the pushback is cleared on a First-Come-First-Served (FCFS) basis. However, if departure metering is active, a pushback is cleared only when the number of aircraft on the ramp or taxiway system is below a critical number N^{ctrl} [45, 15, 17]. After the aircraft is cleared for pushback, 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 take-off on a 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 their Spot and Runway Departure Advisor tool [41, 45, 37]. 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 study 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 study enables faster simulations than detailed models, and it is capable of accurately estimating pushback and take-off time distributions. The objective of this chapter is to analyze the impact of gate assignment on departure metering, and the resolution of the queuing model is sufficient for the analysis.

5.2.2 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, take-off time, taxi-out time, tail number, runway configuration, etc. The data are categorized by departure runway. Frequently used runway configurations are given in Table 6, and the layout of LGA is shown in Figure 49. Most of the time, one runway is used for arrivals and another runway is used for departures. Table 6 shows that runway 13 served departures the most frequently. Precisely, runway 13 operated for 3456 hours (39.5% of the year) and served 83143 pushbacks (47.6% of pushbacks that year). So, the queuing model is calibrated with departures from runway 13.

Table 6: Frequently Used Runway Configuration in LGA

Configuration (Arrival — Departure)	% of Hours	% of Pushbacks
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 %
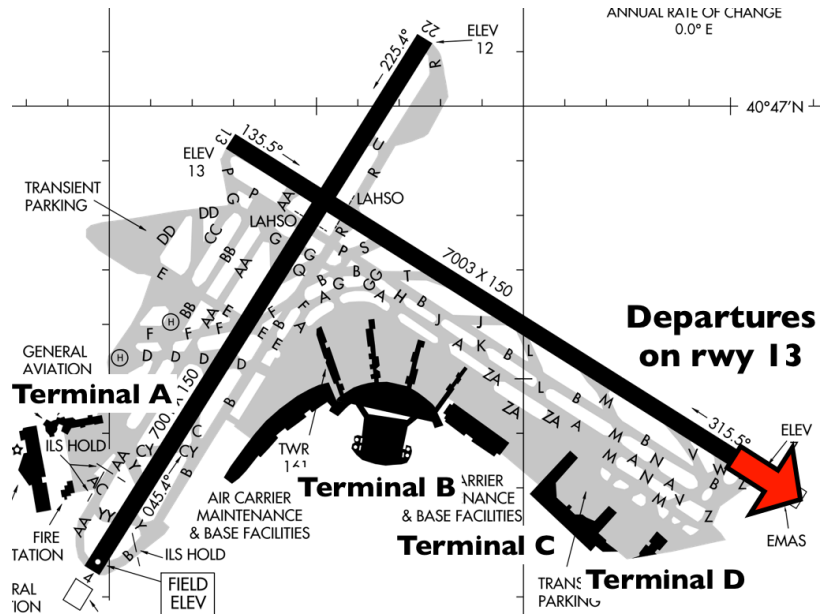
Figure 49: Layout of La Guardia Airport. All departures on runway 13 are modeled, and arrivals are aggregated.

5.2.3 Take-off Model

As Shumsky has shown in [61], the take-off rate is related to N, 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 take-offs 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 [59]. Figure 50 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 take-offs over the next 10 minutes. It is known that arrivals influence departure rates [63]. However, this effect is neglected for the simplicity of analysis.
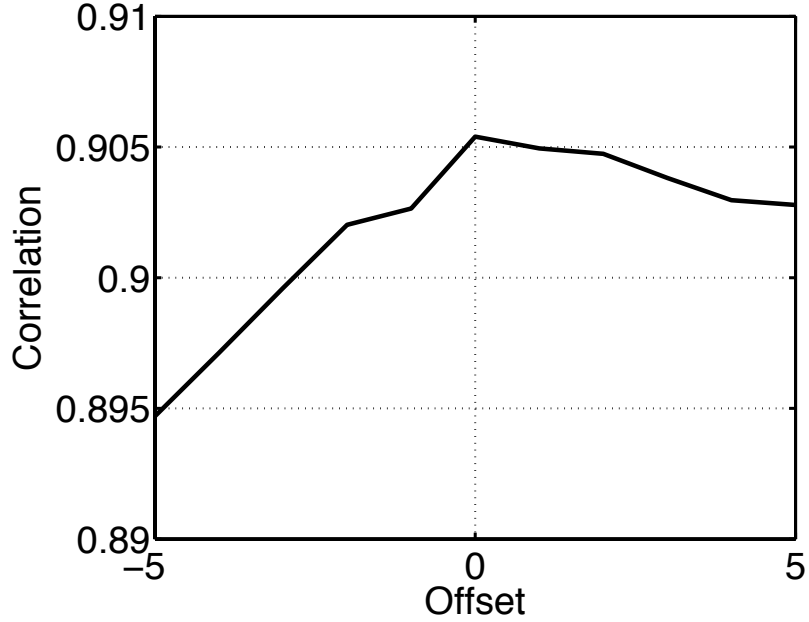
Figure 50: Correlation between $N(t)$ and $T(t + \delta t)$: $N(t)$ best predicts $T(t)$.

Figure 51 shows the average and standard deviation of $T(t)$ according to $N(t)$, where 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 take-off rate are 0.57 aircraft per minute and 0.12 aircraft per minute, respectively. Figure 51 is equivalent to the flow-density curve in the ground transportation literature [24, 66, 20, 40]. Unlike road models where throughput (flow) is limited by road characteristics such as jam density and free flow speed, airport throughput is limited by runway capacity only. In some extreme cases, airport throughput can be seen to decrease, like 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.
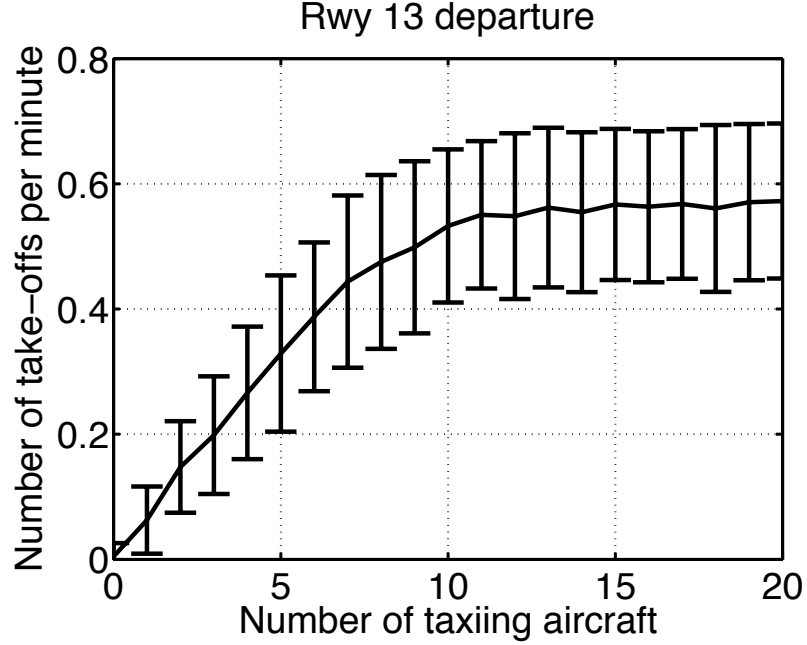
Figure 51: $T(t)$ as a Function of $N(t)$: The vertical bars indicate the standard deviation of $T(t)$ for each $N(t)$.

In order to capture the first and the second moments of $T(t)$, two variables (p_1 and p_2) and three parameters (c_1, c_2, and c_3) are defined. A take-off 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 $1 - p_1 - p_2$.

Then, the runway capacity is expressed

$$\mu = c_1 p_1 + c_2 p_2 + c_3(1 - p_1 - p_2) \tag{48}$$

$$\sigma = \sqrt{\frac{c_1^2 p_1 + c_2^2 p_2 + c_3^2(1 - p_1 - p_2) - \mu^2}{10}}. \tag{49}$$

The three parameters are explored in increments of 0.025 to find the best set of parameters that simulates the distribution of take-off rate at $N = N^*$. The variables

p_1 and p_2 are calculated by Equation (48) and Equation (49). The variables and parameters of the take-off model are given in Table 7.

Table 7: Variables and Parameters of the Take-off 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
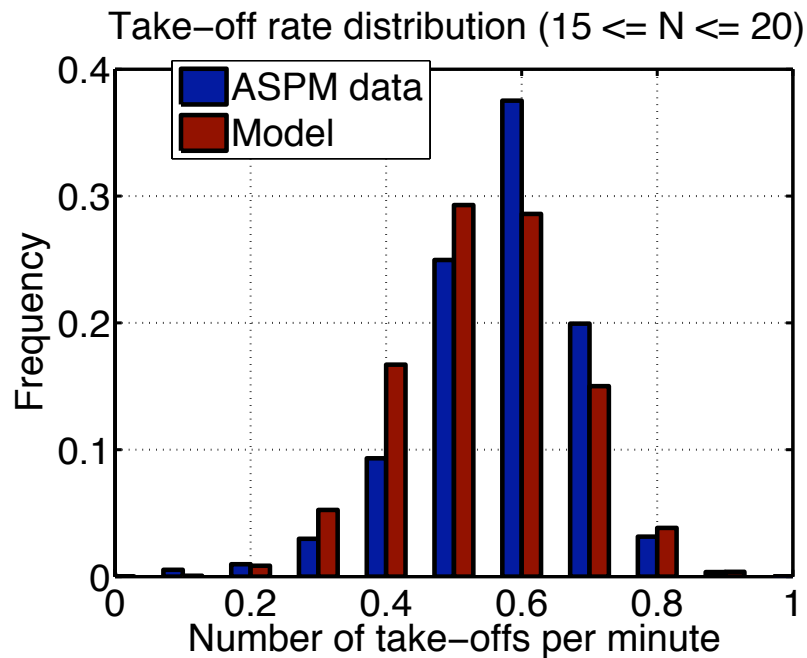
Figure 52: Take-off Rate Distribution at LGA: The take-off model simulates the departure throughput well.

When the runway queue is not empty, the take-off model randomly selects the current take-off rate c according to p_1 and p_2. So, 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 take-off rate c is added to the previous take-off rate, and the largest integer smaller than this cumulative sum of

c is the maximum number of take-off clearances at the current time step. Then, the actual number of take-offs is subtracted from the cumulative sum of c. For example, 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 take-off can be cleared at the current time step. Because there are aircraft in the runway queue, the take-off model clears a take-off. Then, the cumulative sum of c becomes $1.075 - 1 = 0.075$. Note that the take-off model clears only integral number of aircraft. Figure 52 shows the distribution of take-off rates from ASPM data and the take-off model. The throughput of the airport departure model is sensitive to the take-off model.

5.2.4   Taxi-out Time Estimation

Taxi-out times in ASPM data are grouped by each terminal in LGA: Terminal 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 US Airways use terminal C, and Delta Airlines flights use terminal A and D: terminals in LGA are indicated in Figure 49. 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}). So, N_{pb} indicates the number of departures that are on the way to the runway ahead of a pushing back aircraft. Figure 53 shows the means and the standard deviations of taxi-out time according to N_{pb}. The mean 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 $N_{pb} < 3$. A Log-normal distribution is used to model the nominal taxi-out time, and Figures 54-57 show the taxi-out time of each terminal and their Log-normal fits. Figure 54 and Figure 56 show an exceptionally high peak at 12 minutes as these terminals serve mostly small aircraft

such as CRJ and ERJ. According to Simaiakis [64], this high peak is caused by a reporting issue of the ASPM data. Some airlines or aircraft do not participate to record their pushback (Out), take-off (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.
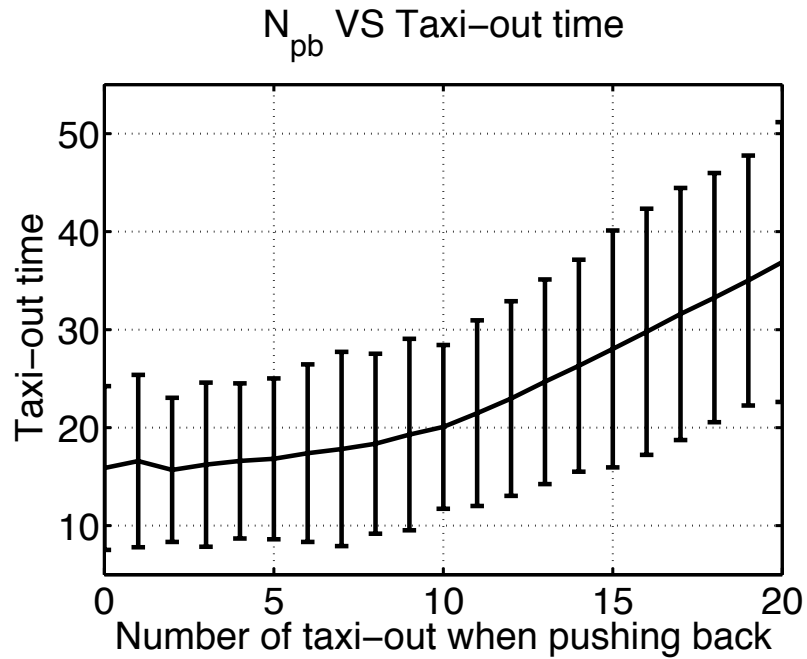
Figure 53: Taxi-out Time according to the Number of Taxi-out Aircraft When an Aircraft Pushes Back: The average taxi-out time does not increase until there are 3-4 taxi-out aircraft.
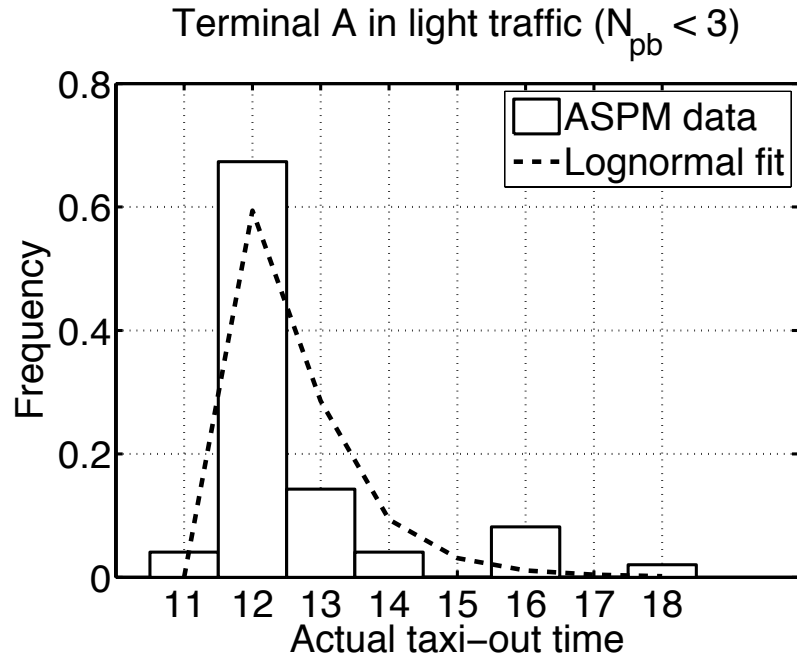
Figure 54: Taxi-out Time of Terminal A in Light Traffic (the number of taxi-out aircraft is fewer than 3.)
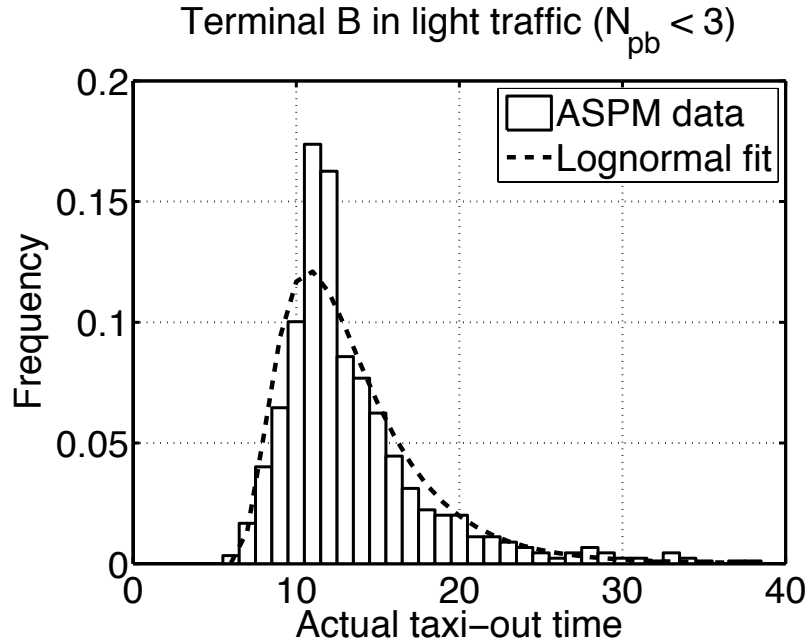
Figure 55: Taxi-out Time of Terminal B in Light Traffic (the number of taxi-out aircraft is fewer than 3.)
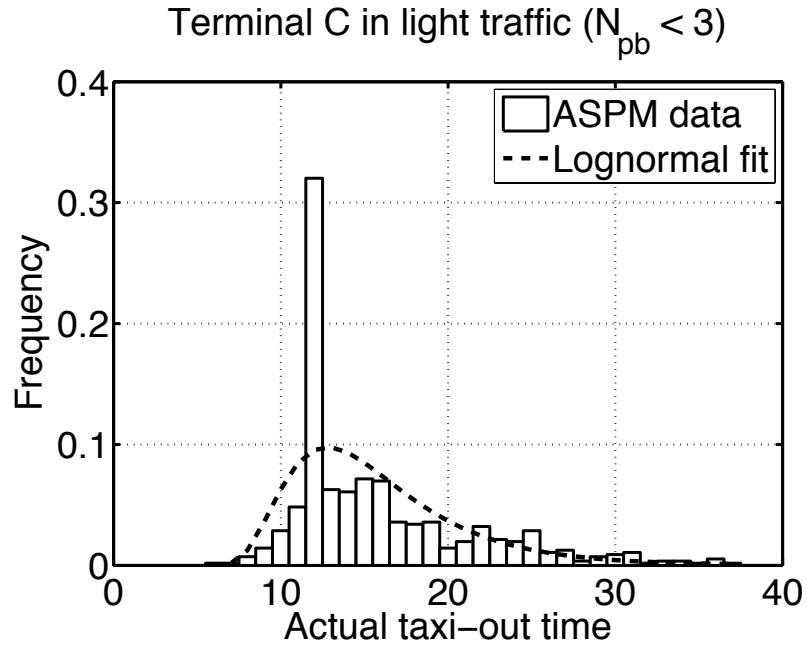
Figure 56: Taxi-out Time of Terminal C in Light Traffic (the number of taxi-out aircraft is fewer than 3.)
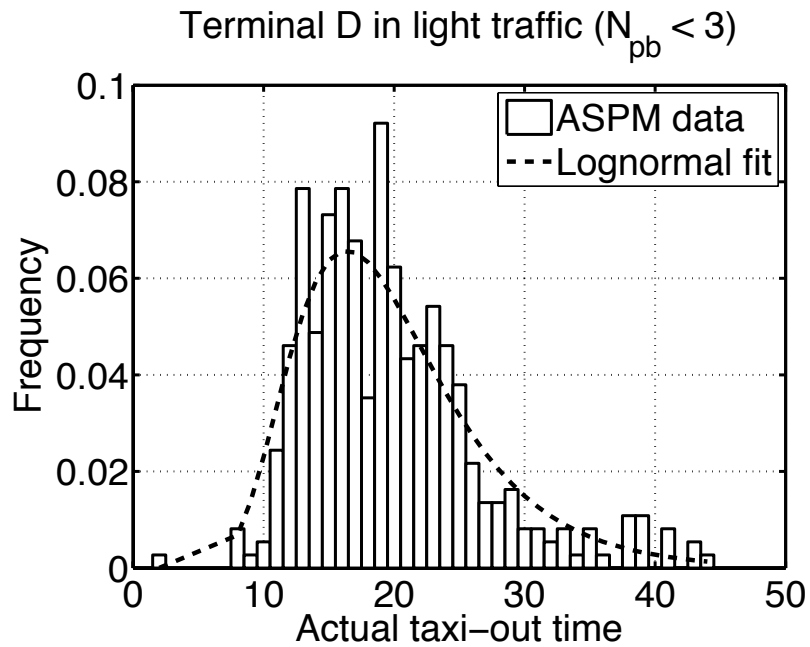
Figure 57: Taxi-out Time of Terminal D in Light Traffic (the number of taxi-out aircraft is fewer than 3.)

5.2.5 Model Validation

The calibrated departure model is validated with departures on runway 13 in 2009. Figure 58 shows the graph of T vs N. The model reproduces the take-off rate well. Figure 59 shows the distribution of N_{pb}. Figures 60-62 show the distribution of taxi-out times in light ($N_{pb} < 3$), medium ($3 \leq N_{pb} < 10$), and heavy ($N_{pb} \geq 10$) traffic. The model reproduces every traffic situation except for a high peak at 12 minutes, which is caused by the ASPM reporting issue along with the high peaks of Figure 54 and Figure 56.
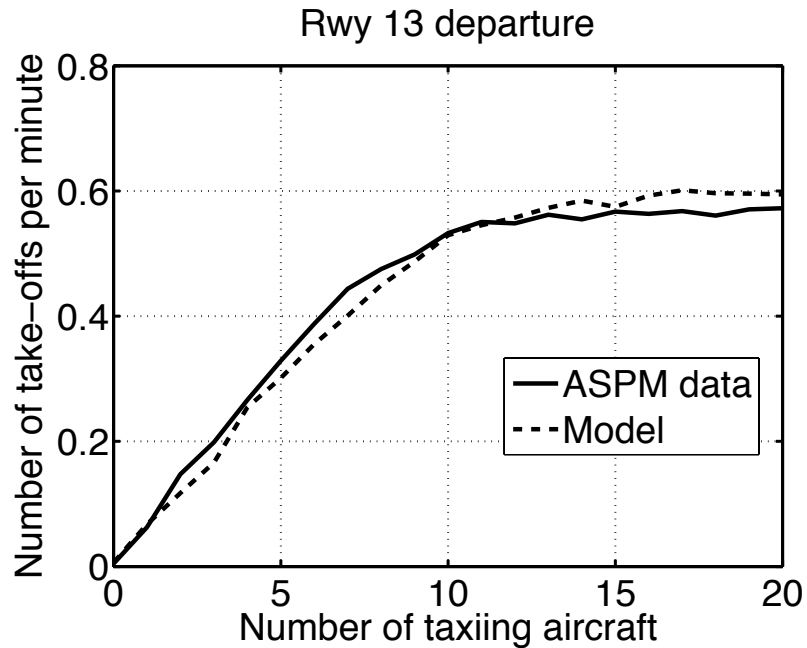
Figure 58: Model Validation: T vs N.
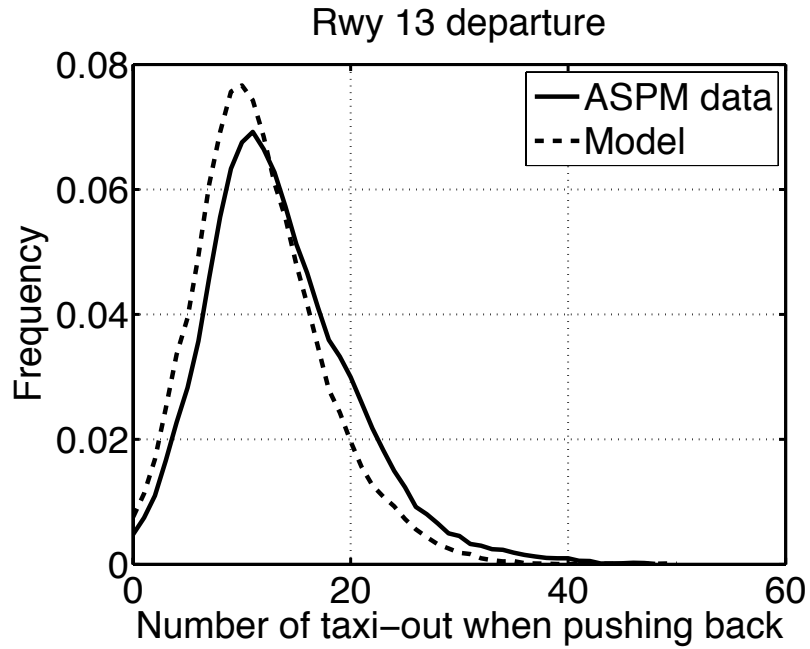
Figure 59: Model Validation: the distribution of N_{pb}.
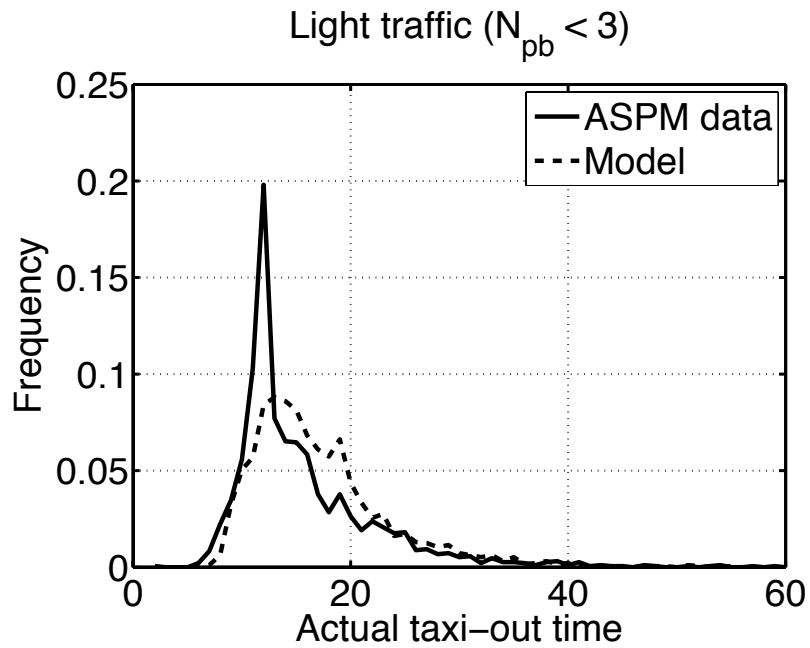
Figure 60: Model Validation: Taxi-out time in light traffic.
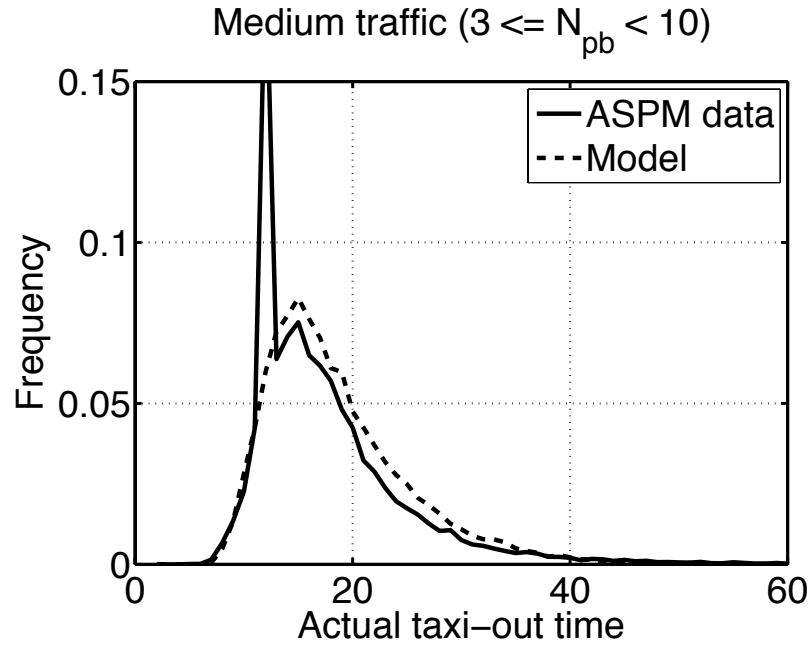
Figure 61: Model Validation: Taxi-out time in medium traffic.

Figure 62: Model Validation: Taxi-out time in heavy traffic.

5.3 Gate Assignment and Departure Metering at La Guardia Airport

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 [33]. The robust gate assignment is an assignment that minimizes the duration of gate conflicts (the third objective of the GAP), and it is based on scheduled flights because airport gates are assigned prior to the actual operation day.

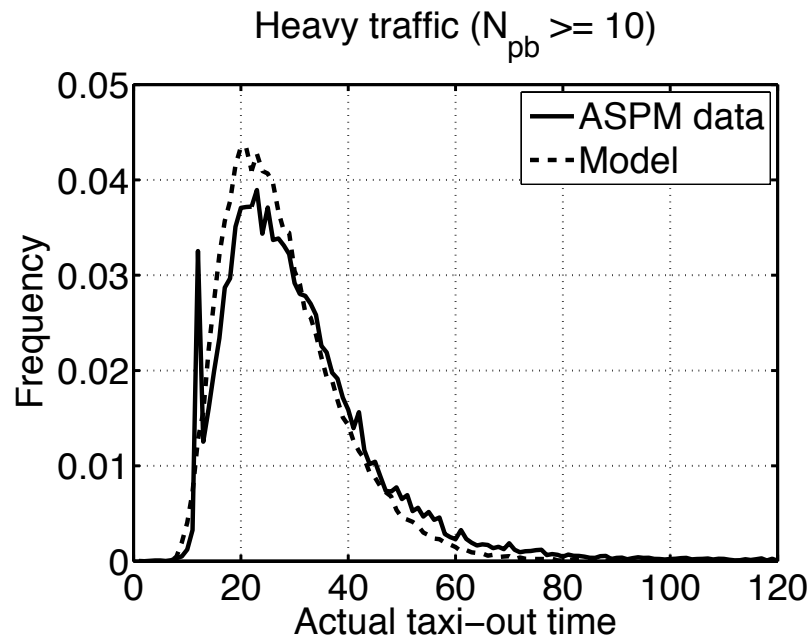The available flight schedules are separated into departures and arrivals, but an arrival and a departure sharing the same aircraft should be assigned to the same gate to eliminate any cost caused by towing the aircraft from one gate to another. So, a departure is paired with an arrival by comparing 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 terminal A and D. In 2012, Delta Airlines began to use gates in terminal C. The data used in this study do not reflect this recent change in LGA.

Table 8 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. Also, smaller

standard deviation with the robust gate assignment indicates that the distribution of gate separation is less dispersed.

Table 8: 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

More specifically, gate separations during a peak time are compared. Figure 63 shows the number of pushbacks for May 10. Seventy minutes from the highest peak at 19:50 are selected as a peak time. Figure 64 shows the distribution of gate separation during the peak time with the current gate assignment. At many gates, the next flight is scheduled to arrive within 50 minutes after the previous flight has departed. And the average gate separation during the peak time is 73 minutes. Figure 65 shows the distribution of gate separation during the peak time with the robust gate assignment, and the average gate separation is 100.6 minutes. From Figure 64 and Figure 65, it is concluded that the robust gate assignment ensures longer gate separation in peak times too.
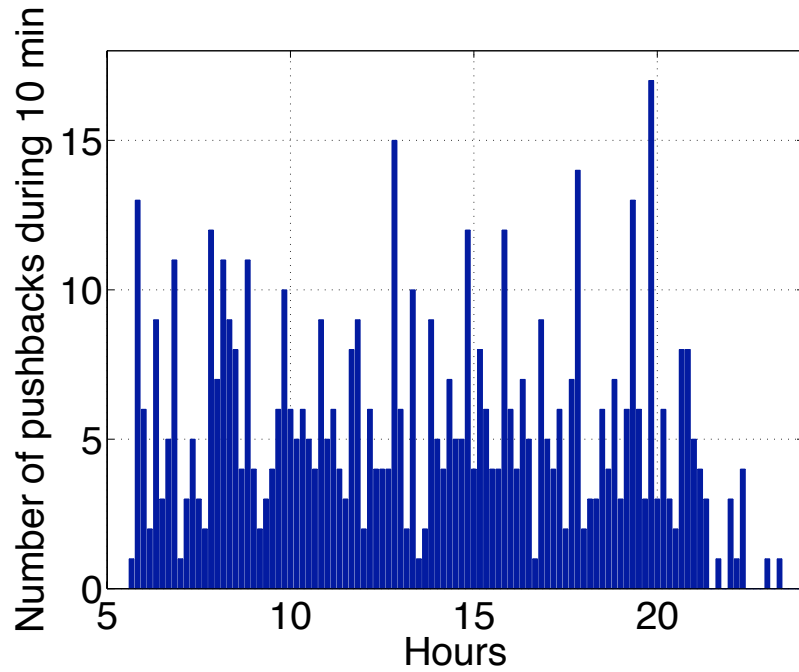
Figure 63: Number of Pushbacks for May 10, 2012 at LGA.
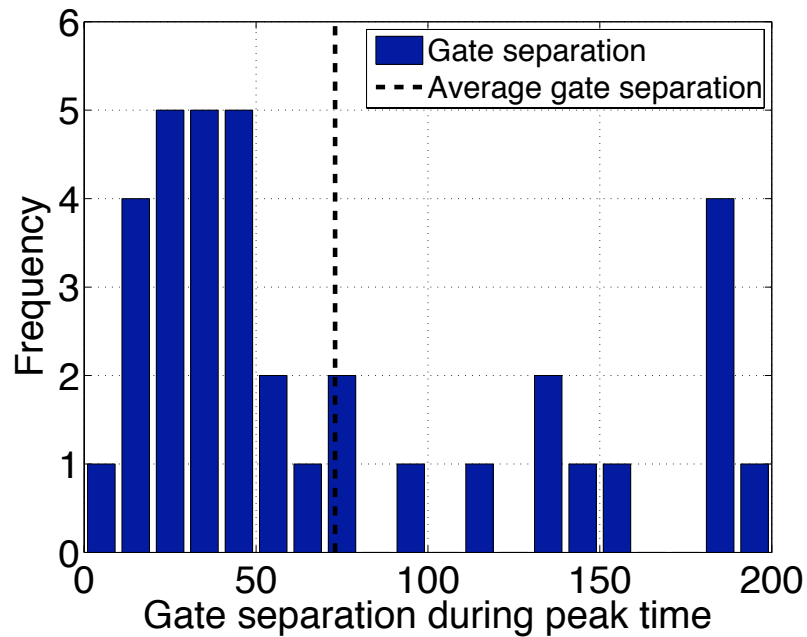
Figure 64: Distribution of Gate Separation during a Peak Time with the Current Gate Assignment: The average gate separation is 73 min.
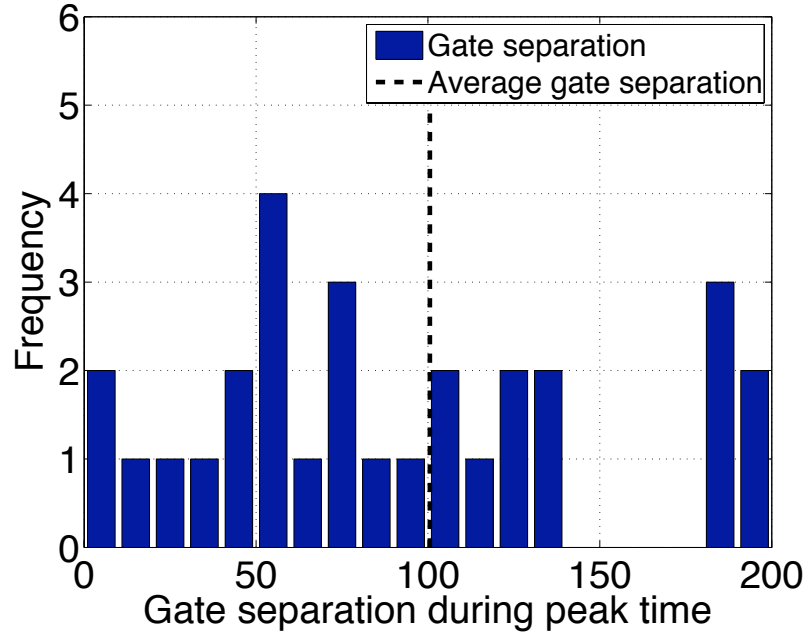
Figure 65: Distribution of Gate Separation during a Peak Time with the Robust Gate Assignment: The average gate separation is 100.6 min.

5.3.1 Simulation Model

The current gate assignment and the robust gate assignment are simulated using an airport departure model. The simulation structure is given in Figure 66. When a departure is ready to push back, it enters the pushback queue. A pushback 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, pushback is not cleared until N is below N^{ctrl}. After the pushback, a taxi-out time is randomly generated according to the departure terminal and the aircraft enters the runway queue. From the runway queue, a take-off is cleared FCFS.
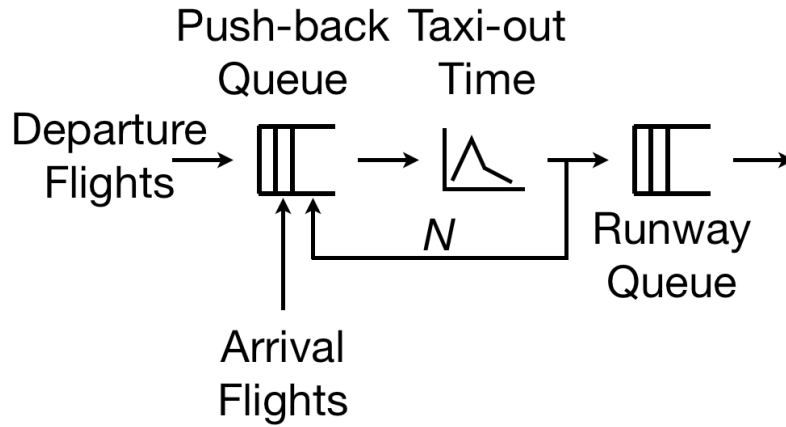
Figure 66: Simulation Structure.

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

5.3.2 Relationship between Taxi-out Times, Gate-holding Times, and $N^{\mathbf{ctrl}}$
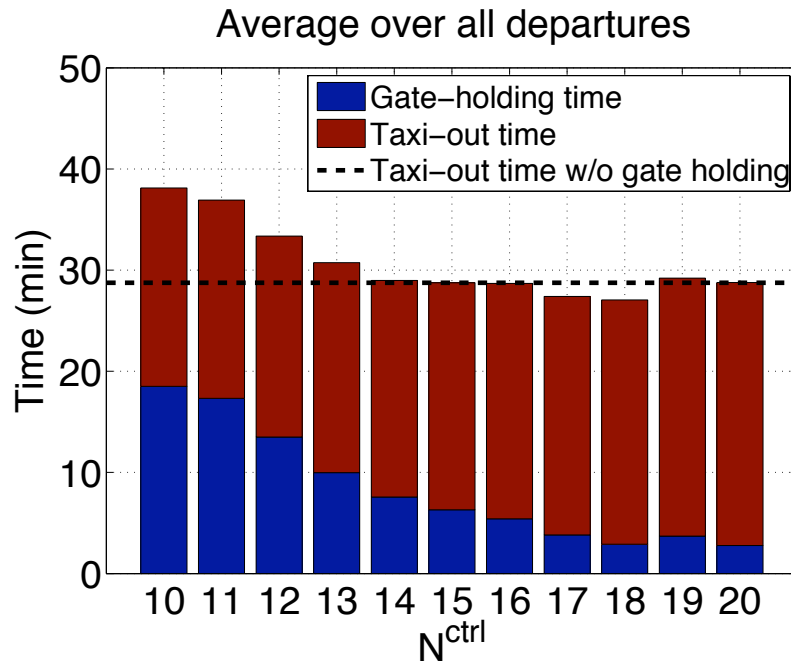
Figure 67: Average Gate-holding Times and Taxi-out Times for the Current Gate Assignment at LGA: The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 14 are similar to the average taxi-out time without departure metering.
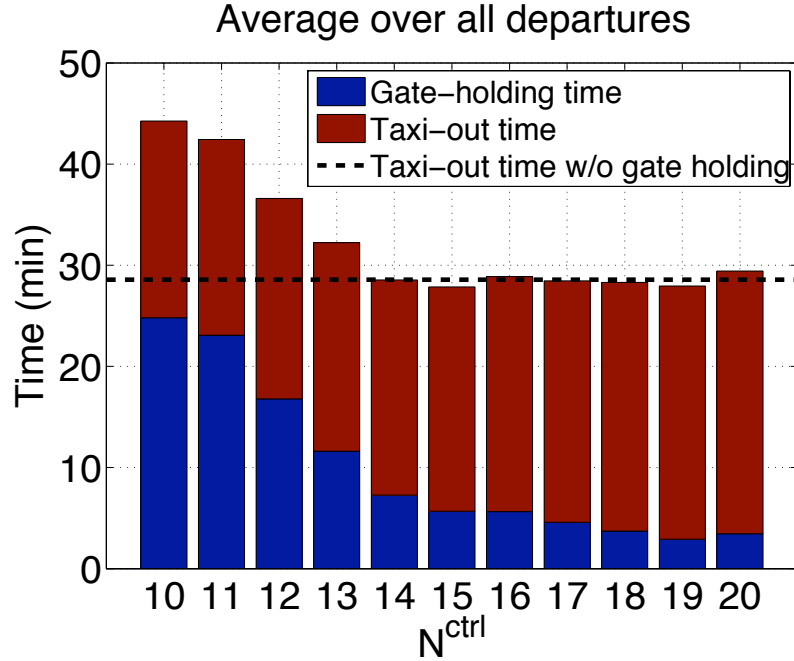
Figure 68: Average Gate-holding Times and Taxi-out Times for the Robust Gate Assignment at LGA: Like Fig. 67, the sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 14 are similar to the average taxi-out time without departure metering.

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. Figure 67 and Figure 68 shows 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. 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. Also, 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. That means 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.
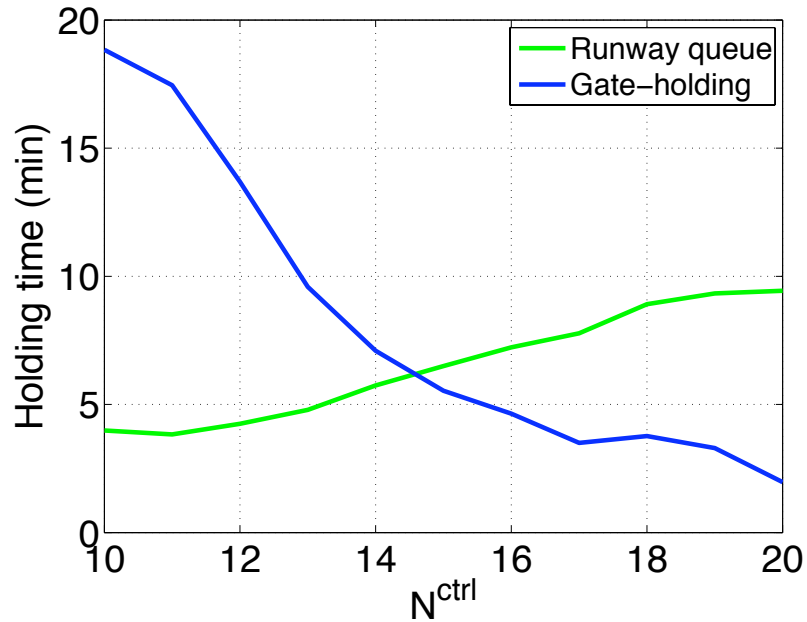
Figure 69: Average Runway Queue Holding Times and Average Gate-holding Times for the Current Gate Assignment at LGA: There is a trade-off between runway queue holding time and gate-holding time.

In addition, runway queue holding times with N^{ctrl} varying from 10 to 20 are shown in Figure 69. As N^{ctrl} decreases, the airport surface becomes less congested with taxi-out aircraft and departures experience less queuing at the runway threshold. At the same time, departures are held at the gates for a longer time. When N^{ctrl} is high, gate-holding time decreases, but queuing time at the runway threshold increases. Hence, there is a trade-off between runway queuing time and gate-holding time.

5.3.3 Impact of Gate Assignment on Departure Metering

Table 9: Impact of Gate Assignment on Departure Metering at LGA

Gate Assignment	Current		Robust	
Departure Metering ($N^{\text{ctrl}} = 14$)	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-holding 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

The impact of gate assignment on departure metering is analyzed. Table 9 compares the impacts of two gate assignments on departure metering. The variable N^{ctrl} is set to 14 with Figures 67-68. With the current gate assignment, departure metering increases the number of occurrences of gate conflict over 3 times compared to no departure metering, and more than half the departures (1267.7 out of 2409) are held at gates for 12.6 minutes on average. Note that the mean gate-holding time is averaged over gate-held departures (1267.7 departures) as opposed to Figures 67-68 where average gate-holding time is computed with every departure, and the mean taxi-out time is averaged over the whole departures (2409 departures). So, the reduction of taxi-out time from departure metering (7.9 minutes) is smaller than the average gate-holding time (12.6 minutes). With the robust gate assignment, 1315.1 out of 2409 departures are held at gates for 13.3 minutes on average. The robust gate assignment induces fewer gate conflicts than the current gate assignment, whether or not departure metering is used, as given in Table 9. The fewer gate conflicts coming from the robust gate assignment are due to the longer mean gate separation, as shown in Table 8. Specifically, the robust gate assignment with departure metering reduces the occurrence of gate conflicts by 78% and 50% without departure metering compared to the current gate assignment. 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 8 and Table 9, 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-holding times (12.6 min for the current gate assignment and 13.3 min for the robust gate assignment). Also, the ratios of the number of gate conflicts to the number of gate-held departures, which are 0.17 for the current gate assignment and 0.08 for the robust gate assignment, support this explanation.

5.4 Gate Assignment and Departure Metering at a Major U.S. Hub Airport

Figure 70 shows the number of daily operations per gate for some busy airports in the world. It is indicated that gates of LGA are the busiest among the busy international airports, and two U.S. major hub airports, Hartsfield-Jackson Atlanta International Airport and Chicago O'Hare Airport, follow LGA. It means that there are potential benefits of departure metering at those hub airports and it is worth analyzing the impact of smart gate assignment on departure metering. Hence, the queuing model is applied to another airport, which is one of the busiest hub airports in the U.S.
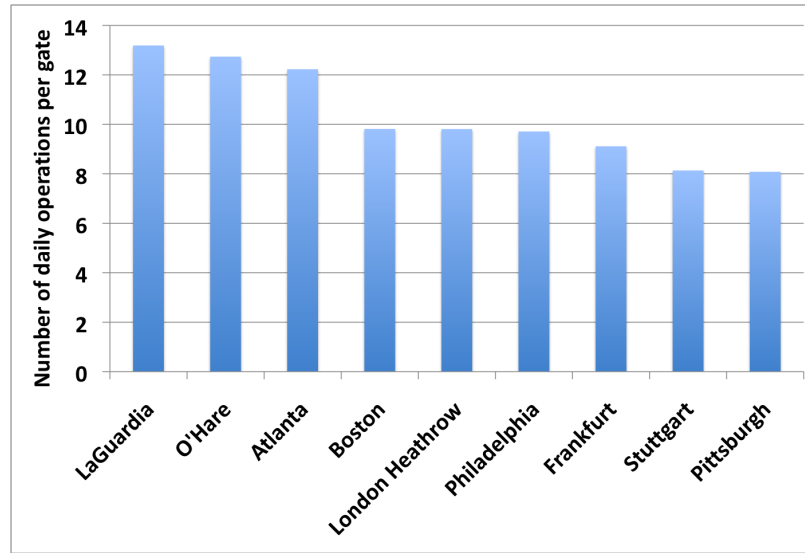
Figure 70: The Number of Daily Operations per Gate for Some Busy International Airports: Higher number indicates higher probability of gate conflicts.

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 5 runways in the airport, and 2 of them accommodate departures most of the time. Figure 71 shows the layout of the airport. The most frequently used runways for departure in 2009 are given in Table 10. 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.

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[1]Names of the airport and airlines are withheld to protect the airlines' data.
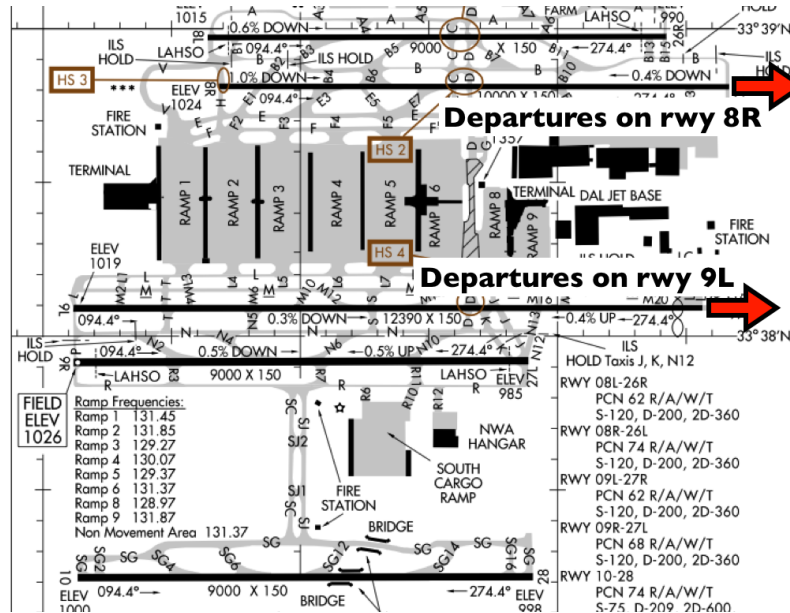
Figure 71: Layout of a Major U.S. Hub Airport. IFR departures on runways 8R and 9L are modeled, and arrivals are aggregated.

Table 10: Frequently Used Runways for Departure at a U.S. Hub Airport

Runways	% of Pushbacks	
26L, 27R	40.4 % (VFR)	8.5 % (IFR)
8R, 9L	26.6 % (VFR)	12.8 % (IFR)

5.4.1 Model Calibration

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. As shown in Figure 72, the number of taxi-out aircraft at time t, $N(t)$, best predicts the number of take-offs over the time periods $[t + 2, t + 11]$. The average and standard deviation of the airport throughput $T(t+2)$ according to $N(t)$ is shown in Figure 73. Similar to Figure 51, $T(t + 2)$ increases with $N(t)$ and is saturated when $N(t)$ is larger than a certain number. It is shown that $T(t + 2)$ drops when $N(t)$ is higher than 70. This drop might indicate gridlock and correspond to what is observed in the ground transportation literature [24, 66] when traffic is very dense: Traffic density

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then replaces runway capacity as the factor that limits airport throughput. The take-off model is calibrated from $T(t + 2)$ when $N(t)$ is in the range of $[40, 50]$, and it is shown in Figure 74. The variables and parameters of the take-off model are given in Table 11.
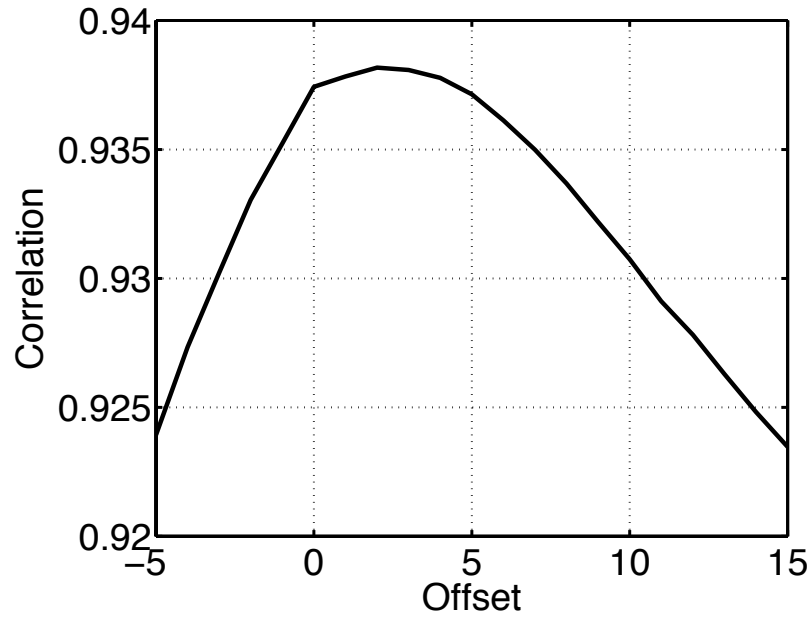
Figure 72: Correlation between $N(t)$ and $T(t + \delta t)$: $N(t)$ best predicts $T(t + 2)$.
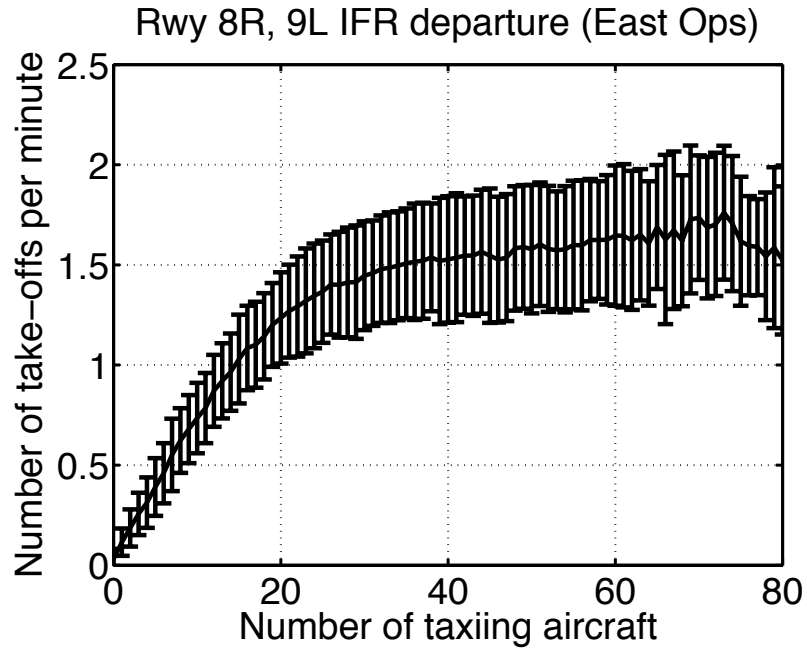
Figure 73: $T(t+2)$ as a Function of $N(t)$: The vertical bars indicate the standard deviation of $T(t+2)$ for each $N(t)$.
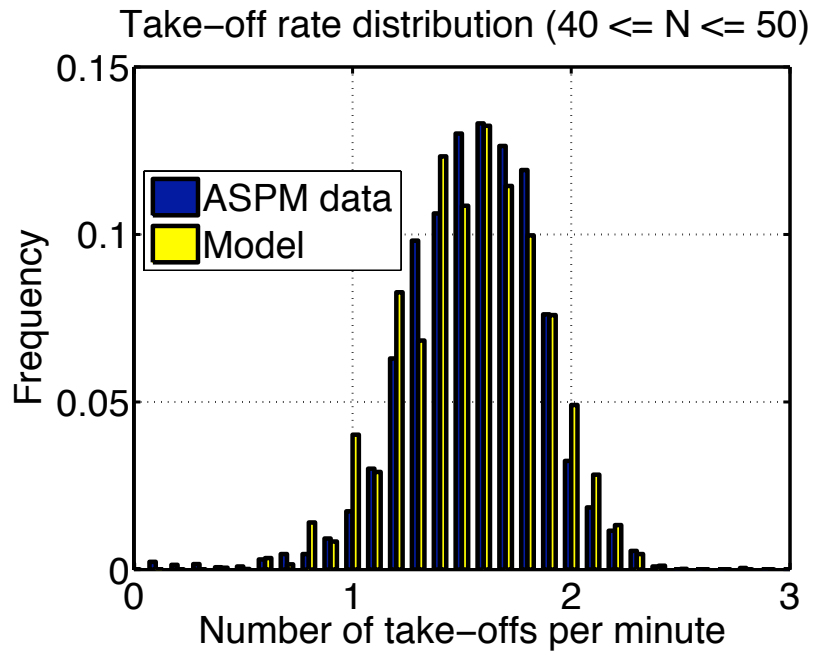
Figure 74: Take-off Rate Distribution at a U.S. Hub Airport: The take-off model simulates the departure throughput well.

Table 11: Variables and Parameters of the Take-off Model

Name	Value
c_1	0 aircraft/minute
c_2	2 aircraft/minute
c_3	3 aircraft/minute
p_1	0.6318
p_2	0.0954

Nominal taxi-out times are obtained from taxi-out times when N_{pb} is less than 15. Figure 75 shows the means and the standard deviations of taxi-out times according to N_{pb}. It is assumed that there is light traffic on the airport surface and taxi-out is unimpeded when $N_{pb} < 15$. Figure 76 and Figure 77 illustrate the distributions of nominal taxi-out times of carrier A and B, and their Log-normal fits. The Log-normal distributions estimate the nominal taxi-out times of carrier A and carrier B well. Airlines other than carrier A and carrier B operate about 12 % of operations at the hub airport, and their gate locations are dispersed over concourses. Hence, taxi-out times of other carriers are aggregated, and Figure 78 shows the distribution of nominal taxi-out times of other carriers and its Log-normal fit.
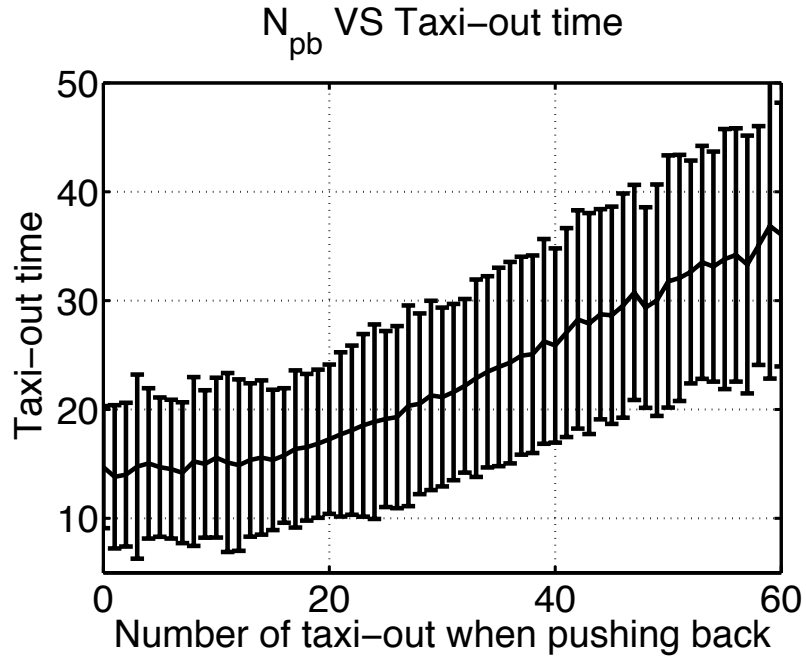
Figure 75: Taxi-out Time according to the Number of Taxi-out Aircraft When an Aircraft Pushes Back: The average taxi-out time does not increase until there are 14-15 taxi-out aircraft.
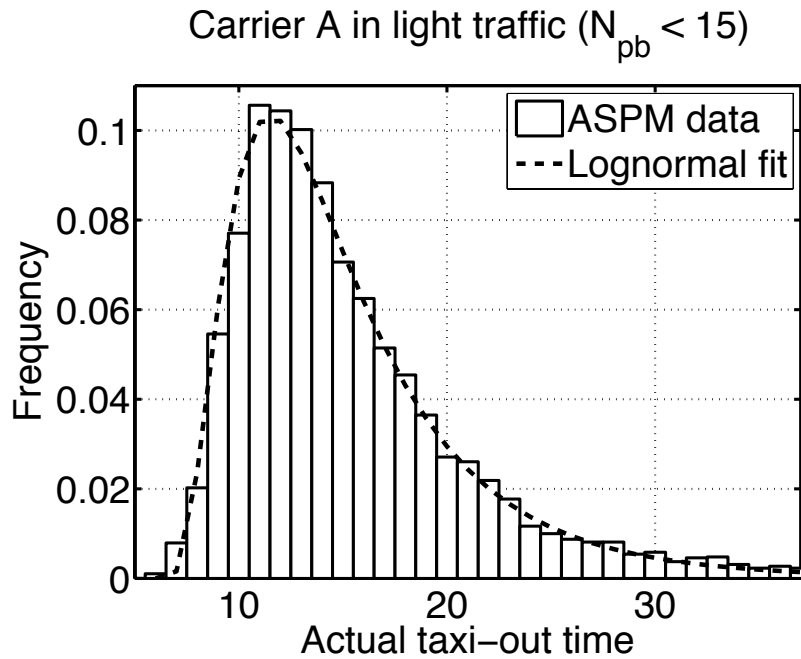
Figure 76: Taxi-out Time of Carrier A in Light Traffic (the number of taxi-out aircraft is fewer than 15.)
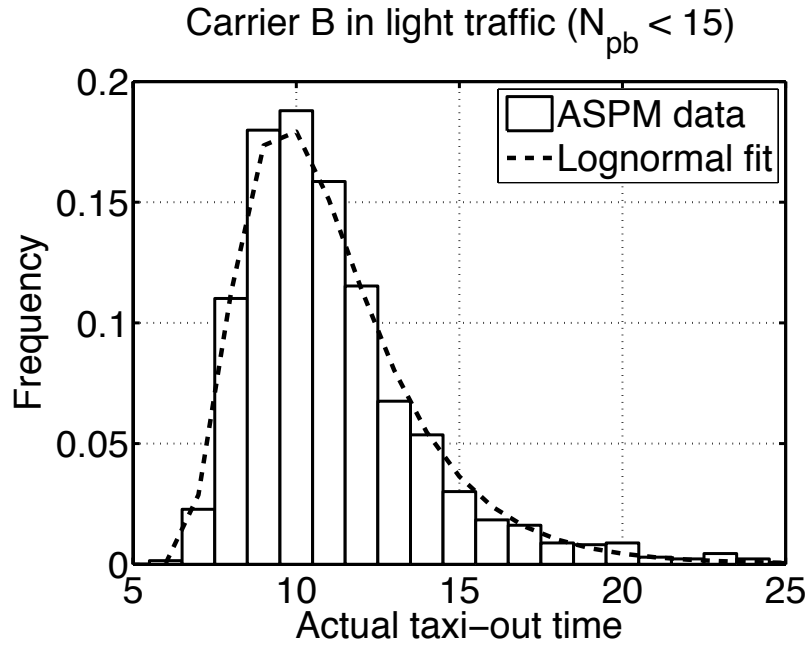
Figure 77: Taxi-out Time of Carrier B in Light Traffic (the number of taxi-out aircraft is fewer than 15.)
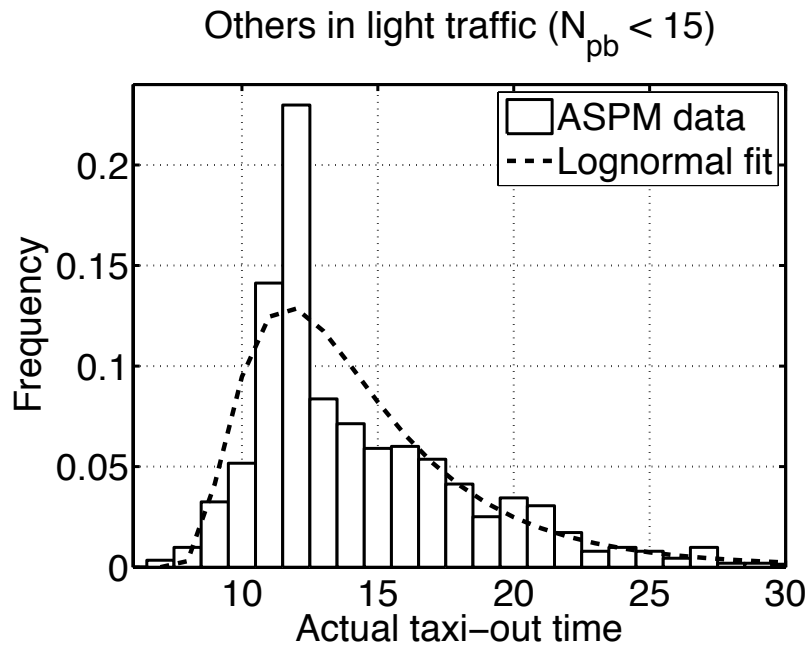
Figure 78: Taxi-out Time of Other Carriers in Light Traffic (the number of taxi-out aircraft is fewer than 15.)

5.4.2 Model Validation

The calibrated departure model is validated with departures on runways 8R and 9L. The T vs N curve is given in Figure 79. It is shown that the model reproduces the saturation of the departure throughput well. Also, the model simulates surface congestion as shown in Figure 80. The quantity N_{pb}, which is the number of taxi-out aircraft when an aircraft pushes back, indicates the congestion level of the airport surface when each aircraft leaves the gate. Figures 81-83 show the distributions of taxi-out times in light ($N_{pb} < 15$), medium ($15 \leq N_{pb} < 40$), and heavy ($N_{pb} \geq 40$) traffic. Heavy traffic is determined from $N(t)$ when airport throughput begins to be saturated in Figure 73. From Figures 79-83, the model is successful at simulating departure operations in every traffic situation.
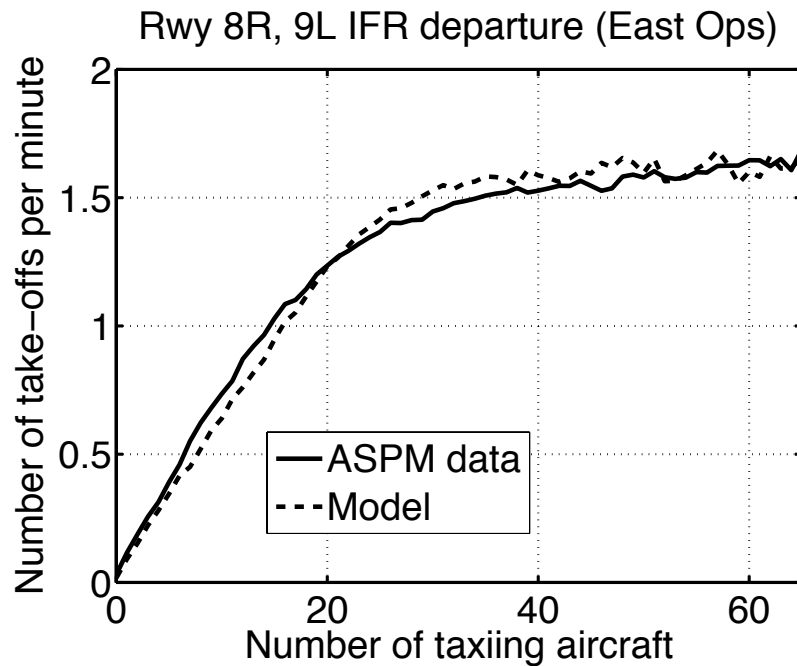
Figure 79: Model Validation: T vs N.
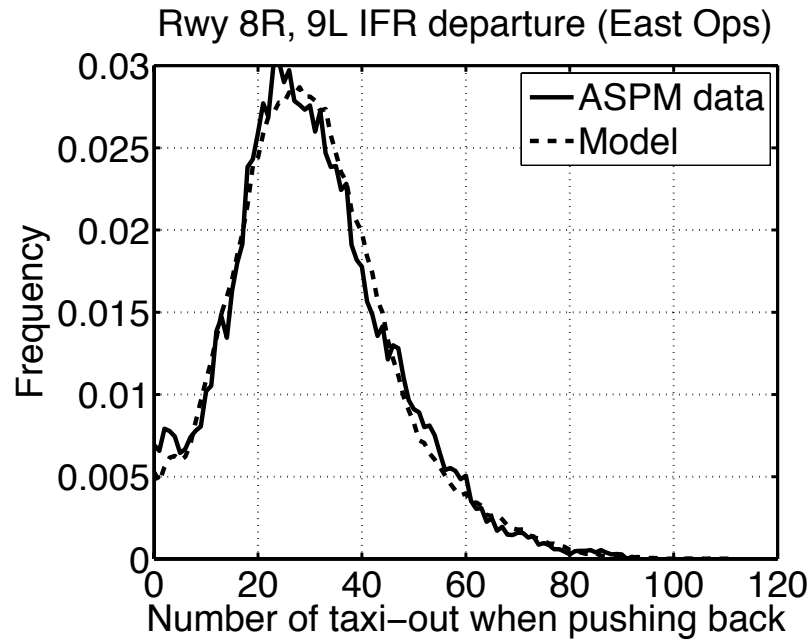
Figure 80: Model Validation: the distribution of N_{pb}.
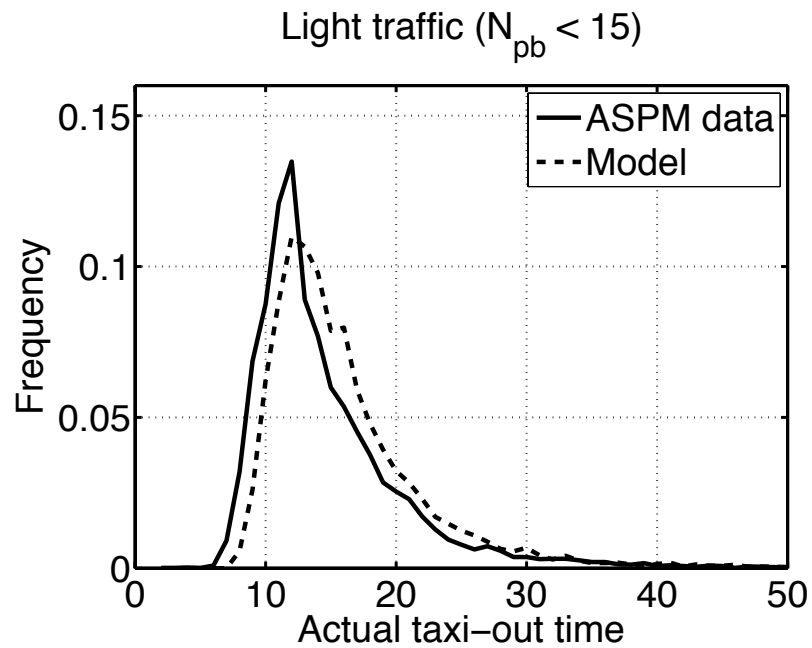
Figure 81: Model Validation: Taxi-out time in light traffic.
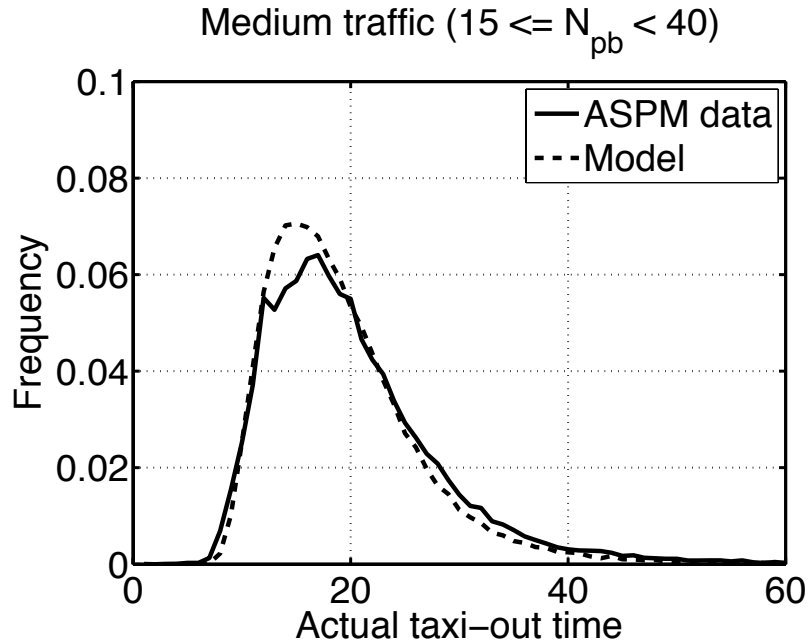
Figure 82: Model Validation: Taxi-out time in medium traffic.
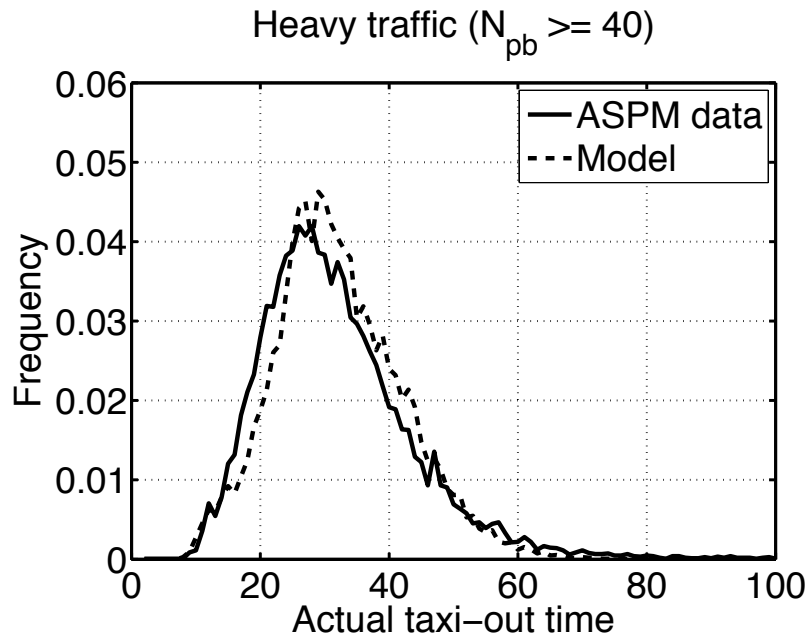
Figure 83: Model Validation: Taxi-out time in heavy traffic.

5.4.3 Impact of Gate Assignment on Departure Metering

Two gate assignments are assessed: the current gate assignment and the robust gate assignment. The current gate assignment is obtained from the carrier A as given in

Section 4.4.1, and the robust gate assignment is given in chapter 4. The relationship between taxi-out times, gate-holding times, and N^{ctrl} is illustrated in Figures 84-85. From the figures, N^{ctrl} is set to 33, but Figure 73 shows that the take-off rate still increases for N greater than 33. It means that N^{ctrl} is smaller than N^* and we may lose some departure throughput with the chosen value of N^{ctrl}. Then, taxi-out times are increased. As shown in Figures 84-85, however, the taxi-out time without departure metering is equal to the sum of taxi-out time and gate-holding time for N^{ctrl} equal to or greater than 33. That is, the increment of taxi-out time due to the throughput loss is not significant. In addition, if N^{ctrl} is increased to 40 or even higher based on Figure 73, a benefit of departure metering, which is the reduction of taxi-out time, becomes negligible because the majority of departures would be cleared to push back without being held at gates.
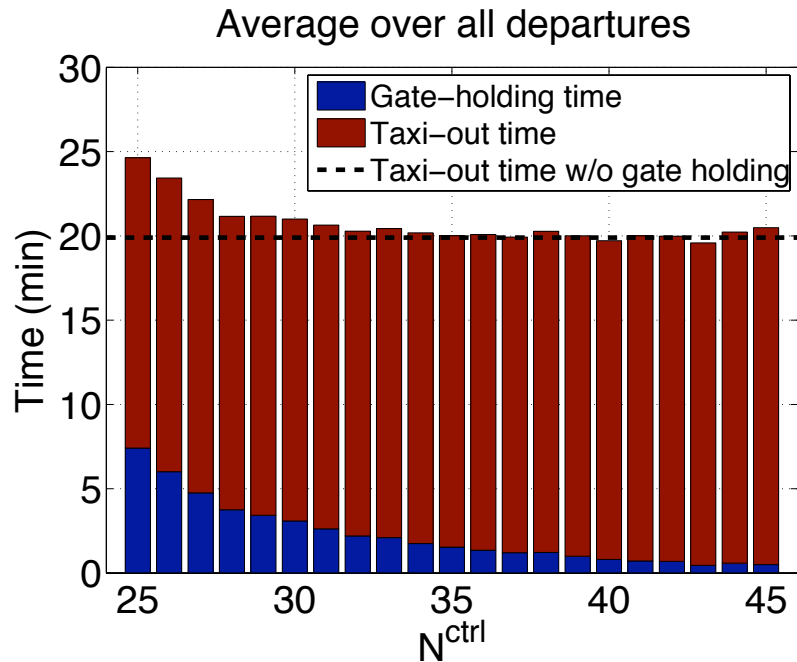
Figure 84: Average Gate-holding Times and Taxi-out Times for the Current Gate Assignment at a U.S. Hub Airport: The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 33 are similar to the average taxi-out time without departure metering.
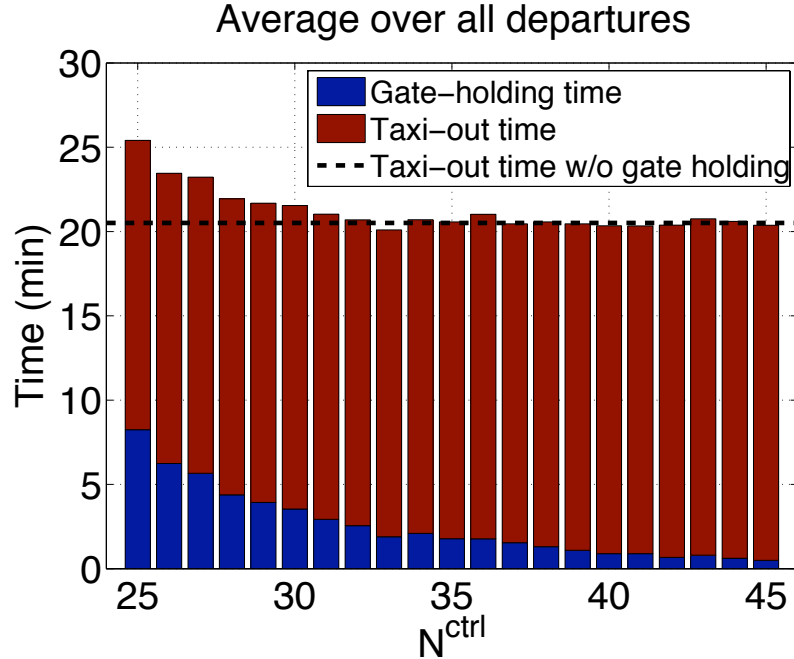
Figure 85: Average Gate-holding Times and Taxi-out Times for the Robust Gate Assignment at a U.S. Hub Airport: The sums of gate-holding time and taxi-out time for N^{ctrl} equal to or greater than 33 are similar to the average taxi-out time without departure metering.

Table 12 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 12 are similar to those in Table 9, 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, as compared to 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 ($N_{pb} < 40$) as shown in Figure 86, and it is why the reduction of taxi-out times is smaller than LGA.

Table 12: Impact of Gate Assignment on Departure Metering at a U.S. Hub Airport

Gate Assignment	Current		Robust	
Departure Metering ($N^{\text{ctrl}} = 33$)	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-holding 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
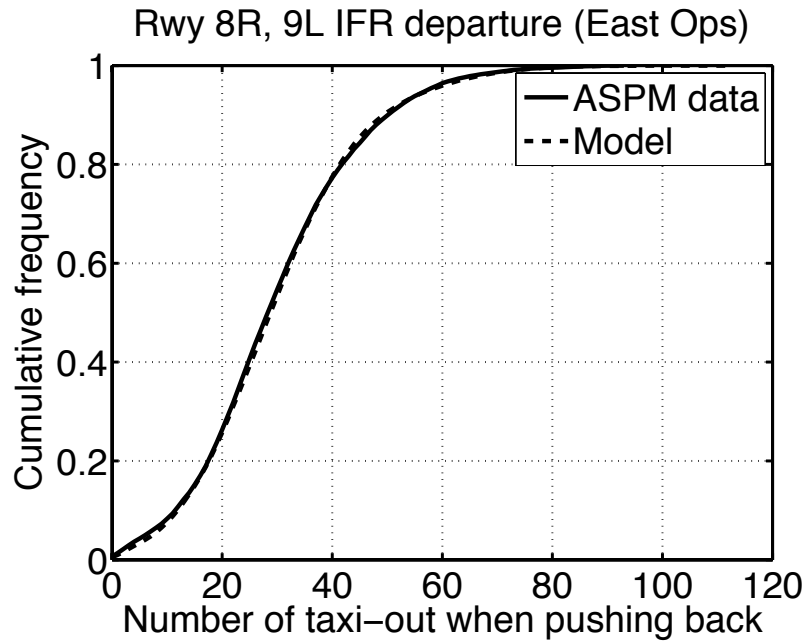
Figure 86: Cumulative Distribution of N_{pb}: About 70-75 % of the departures are cleared to push back when the number of taxi-out aircraft is fewer than 40, which corresponds to the throughput saturation point.

5.4.4 Passenger Transit Time and Departure Metering

The majority of passengers at hub airports are there to transfer their flights as opposed to LGA. For example, 64.2% of passengers at Hartsfield-Jackson Atlanta International

Airport in 2009 were transfer passengers [5]. Hence, the change of gate assignments influences passengers' transit time at the airport terminal. Especially, the consequence will be significant to transfer passengers because their transit routes depend entirely on the gate assignments.

As shown in chapter 4, there is a trade-off between passenger transit time and the robustness of gate assignment. Therefore, it is expected that passengers walk longer due to the change of gate assignments while the number of gate conflicts is reduced. Figure 87 compares average transit time per passenger with the current gate assignment, the robust gate assignment, and the balanced gate assignment. The balanced gate assignment corresponds to $(w_{transit}, w_{taxi}, w_{robust}) = (0.2, 0.2, 0.6)$ as given in chapter 4. As expected, the robust gate assignment increases passenger transit time.
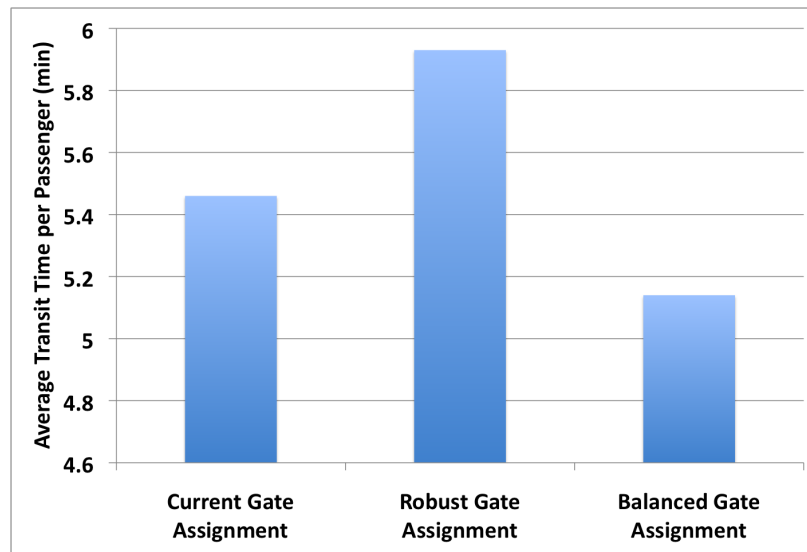
Figure 87: Average Transit Time in Minutes per Passenger with the Current Gate Assignment, the Robust Gate Assignment, and the Balanced Gate Assignment for May 1st, 2011.

Figure 88 compares the number of gate conflicts of three gate assignments. The robust gate assignment reduces the number of gate conflicts compared to the current gate assignment whether or not departure metering is active. The balanced gate

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assignment is more robust than the current gate assignment as given in chapter 4, while reducing passenger transit time. As a result, the balanced gate assignment helps reap the benefits of departure metering by reducing the number of gate conflicts as shown in Figure 88 as well as accommodating passengers' needs by reducing passenger transit time as shown in Figure 87, compared to the current gate assignment. In addition, the balanced gate assignment induces fewer taxi times and delays on ramps as given in Figure 48.
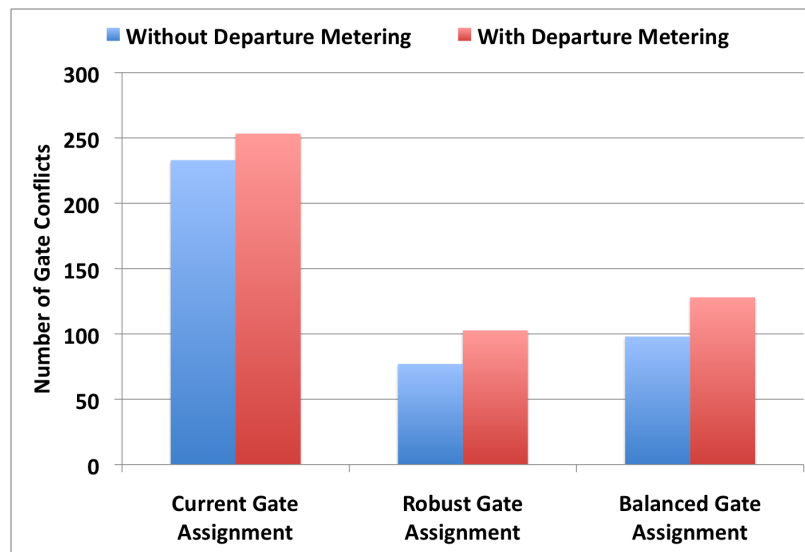
Figure 88: Number of Gate Conflicts with the Current Gate Assignment, the Robust Gate Assignment, and the Balanced Gate Assignment for May 1st, 2011.

5.5   Conclusion

This chapter analyzed the impact of gate assignment on departure metering. In order to simulate the airport departure process, a queuing model is proposed, consisting of a pushback 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 analyzed.

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 study, the influence of arrival rate on take-off rate is neglected, but indeed high arrival rate reduces take-off 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 study provides lower bounds on the performance under smart gate assignment.

However, the robust gate assignment increases passengers' transit time because there is a trade-off between the robustness of gate assignment and passenger transit time. A balanced gate assignment, which is presented in the previous chapter, is also analyzed, and it is shown to manage gate conflicts as well as passenger transit time successfully.

CHAPTER VI

CONCLUSION

6.1 Summary of This Dissertation

This dissertation studies airport operations around ramp areas by means of gate assignment. Gate assignment influences both air-side and land-side operations because passengers board and disembark from aircraft at gates. Gate assignment also influences both departure and arrival operations because arrival operations are completed and switched to departure operations at gates. Hence, smart gate assignment helps improve the efficiency, robustness, and flexibility of airport operations.

An airport is one of the bottlenecks of the air transportation system. As indicated by the 2011 FAA forecast, passenger air traffic is expected to grow, but at the same time airport capacity is not likely to satisfy the increasing demands of air traffic due to limited resources. Construction of new runways or runway expansion will increase the capacity of the airport, but it costs a huge amount of money and such an expansion or construction project is not always possible. So, it is sometimes necessary to manage congestion at an airport given the current airport resources.

This dissertation answers three research questions. The first research question is to distinguish the impact of gate assignment on ramp congestion and how to improve the efficiency of traffic flow on the ramp by proper gate assignment. First, an observation-based ramp operation model is presented to understand dynamics of ramp operations and relationships between gate assignment and ramp congestion. Ramp operations at Hartsfield-Jackson Atlanta International Airport are observed in nominal operational conditions as well as in disturbed operational conditions. Because gate locations determine taxi routes on the ramp, taxi times on the ramp are dependent on gate

assignment. If a taxi route interferes with another taxi route, taxi delays occur. Proper gate assignment reduces the number of interferences between taxi routes by separating taxi routes on the ramp. Consequently, smart gate assignment reduces ramp congestion and improves the efficiency of traffic flow on the ramp.

The second research question is how to concurrently satisfy various objectives of gate assignment. In this dissertation, three objectives are presented: Minimizing passenger transit time, minimizing taxi time on the ramp, and maximizing the robustness of gate assignment. The second objective is proposed by the author in order to address the first research question. Two fictitious airports and a major U.S. hub airport are used to analyze the impacts of gate assignment on passengers, aircraft and operations. The gate assignment problem is solved by Tabu search algorithm with two neighborhood search moves. It is shown that there are trade-offs among the objectives of gate assignment. Hence, it is not possible to minimize all the objectives at the same time. This dissertation proposes a gate assignment that balances three objectives of gate assignment in consideration of the trade-offs. The balanced gate assignment is compared to a real-world gate assignment, and it is shown that all the metrics are improved by the balanced gate assignment.

The last research question is to distinguish the impact of gate assignment on departure operations and how to improve the efficiency and flexibility of airport operations by proper gate assignment. Departure metering is an approach of collaborative decision making to reduce taxi delays and emissions in the departure process by holding some departures at their gates, while maintaining airport departure throughput. The benefits of departure metering are oriented at the utilization of gate separation to some extent where it can be detrimental to the free access of arriving flights to the terminals. For the analysis of the impact of gate assignment on departure metering, departure operations at New York La Guardia Airport and the major U.S. hub airport are simulated. Results show that robust gate assignment helps enjoy the benefits

of departure metering by dispersing the distribution of gate separation, which leads to fewer numbers of gate conflicts. However, as addressed in the second research question, robust gate assignment increases passenger transit time in return. Thus, the balanced gate assignment is assessed and shown to manage gate conflicts as well as passenger transit time successfully.

This dissertation contributes to airport research by suggesting a promising improvement of the efficiency of traffic flow on the ramp, proposing a strategy that balances passengers' transit time, taxi time on the ramp, and the robustness of gate assignment, and providing a strategy that improves the efficiency of departure operations at congested airports with limited gate resources through smart gate assignment.

6.2   Suggestions for Future Research

The calculation (or estimation) of taxi times and delays in this dissertation is based on flight schedules. It is obvious because gates are assigned prior to the day of operation in the U.S., but the accuracy of the estimates is so limited. In order to improve the accuracy of the estimation of taxi times and delays, one should take uncertain delays into account and provide a stochastic model to estimate taxi routes of aircraft on the ramp. Moreover, future research should expand the model into taxiway systems because gate location influences taxi route not only on the ramp but also on the taxiway. By the expanded analysis of the relationship between taxi routes and gate assignment, we make one step further toward an integrated airport model that covers both air-side and land-side operations.

In this dissertation, three metrics assessing passengers' experience are applied equally to all flights and passengers. Sometimes, there are very important passengers or flights that airlines want to accommodate with priority. Also, the value of one minute can differ from one passenger or flight to another. The author suggests future research that enables airlines or an authority who assigns gates to apply weight factors

to each flight or group of passengers. In addition, the distribution of gate separation is more important during peak times than off-peak times. This is especially true when departure metering is active. Departure metering holds departures at their gates when the airport surface is too congested, which occurs during peak times. Figure 89 shows the number of pushbacks during 10 minutes at the hub airport whose gate assignment is analyzed in chapter 4. Simulation results show that the majority of gate conflicts occur during the afternoon peak time (13:00-15:10) and at night (22:30-24:10). Future research distinguishes peak times of the day and focuses on the robustness of gate assignment during peak times.
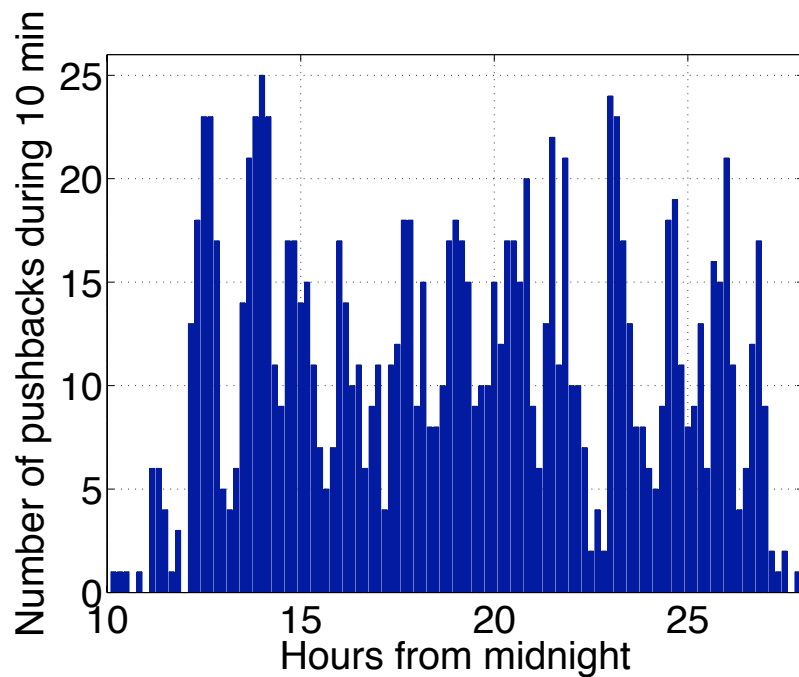
Figure 89: Number of Pushbacks During 10 Minutes at a U.S. Hub Airport.

Another future area of research is gate reassignment. When an aircraft lands but the assigned gate is not released yet, the airline will choose one of the following resolutions:

- Keep the aircraft waiting at a parking spot or on the ramp.

- Reassign the aircraft to another gate, at which gate separation is enough so the

next gate schedule may be unaffected.

- Reassign not only the aircraft but also a subset of aircraft.

The first option enables the airline to retain the original gate assignment, but it is available only if the corresponding gate can be released shortly. The second and third option reassign the aircraft to another available gate. The difference between the two options is whether the reassignment will induce other reassignments. If the free time of the new gate is enough to insert additional aircraft, the airline is able to assign the gate without altering subsequent gate schedules. Because gate schedules are tight in general, however, the second option is not necessarily available. Under these circumstances, the airline wants to minimize the impact of gate reassignment. This area of future research will determine additional cost to airlines and passengers due to gate reassignment and suggest an intelligent recovery plan.

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