Modeling and Control of the
Departure Process of Congested Airports
by
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Ingénieur des Arts et Manufactures
Ecole Centrale Paris (1994)

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Abstract

A simple queueing model of departure operations at congested airports is proposed. This model is calibrated and validated in the case of Boston Logan airport, using runway configuration and traffic data from the Airline Service Quality Performance (ASQP) dataset. The model is then used to evaluate preliminary departure control schemes aimed at alleviating congestion on the airport surface. The potential impact of these control schemes on direct operating costs, environmental costs and overall delay is quantified and discussed.

This thesis also demonstrates that the ASQP dataset does not record enough traffic to precisely identify arrival-departure interaction effects, which results in large uncertainties in the departure model. Since more complete datasets could become available in the near future, the thesis shows how such datasets could be used to reduce the departure model uncertainties.

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And last but not least, many thanks to Tanya for her patience and understanding during the preparation of this thesis.
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**Table of symbols**

\[
\begin{align*}
A(t) & = \text{number of aircraft reaching the runway queue during period } t. \\
A_i(t) & = \text{number of jet aircraft of airline } i \text{ arriving at the gates during time period } t. \\
a & = \text{departure rate of the runway system.} \\
C(t) & = \text{number of aircraft which are cleared to push back by the airport tower controllers during time period } t. \\
C_{dep}(t) & = \text{capacity of the departure runways during period } t. \\
\bar{C}_{dep}(t) & = \text{moving average of the departure capacity during time period } t. \\
\bar{C}_{arr}(t) & = \text{moving average of the arrival capacity during time period } t. \\
c & = \text{departure capacity of the runway system over one time period} \\
& \quad \text{if it is available for take-off.} \\
d & = \text{arrival rate of the runway system.} \\
\Delta_i(D) & = \text{difference between } \gamma_i(D) \text{ and } \lambda_i(D). \\
\delta_i(t) & = \text{difference between } g_i(t) \text{ and } g_i^0(D). \\
\tilde{\delta}_i(t) & = \text{difference between } \tilde{g}_i(t) \text{ and } \tilde{g}_i^0(D). \\
\tilde{e}_{i,j}(N_c) & = \text{under the control law with parameter } N_c, \text{ number of time periods in a year when airline } i \text{ would have needed exactly } j \text{ more gates to avoid a gate shortage.} \\
G_i & = \text{maximum number of jet aircraft that airline } i \text{ can accommodate at any time.} \\
g_i(t) & = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of time period } t. \\
g_i^0(D) & = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of day } D. \\
\tilde{g}_i(t) & = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of time period } t \text{ in a simulation run.}
\end{align*}
\]
\( \bar{y}_i^0(D) \) = number of jet aircraft of airline \( i \) parked at the gates (or on a ramp or in a hangar) at the beginning of day \( D \) in a simulation run.

\( \gamma_i(D) \) = maximum of \( \delta_i(t) \) over day \( D \).

\( GQ(t) \) = number of aircraft which have been cleared by the airport tower controllers at or before period \( t \) but are still being held at the gate at the end of period \( t \).

\( \bar{L}_5(t) \) = moving average of the arrival (or "landing") rate over the time periods \( (t + 1, t + 2, \ldots, t + 11) \).

\( \lambda_i(D) \) = minimum of \( \delta_i(t) \) over day \( D \).

\( N(t) \) = number of departing aircraft on the taxiway system (or "taxiway loading") at the beginning of period \( t \).

\( N_c \) = value of \( N(t) \) above which the departure control law stops pushbacks.

\( N_{PB}(k) \) = value of \( N(t) \) when aircraft \( k \) pushes back.

\( N_{sat} \) = value of \( N(t) \) for which the take-off rate saturates.

\( P(t) \) = number of pushbacks that actually take place during period \( t \).

\( P_i(t) \) = number of jet aircraft of airline \( i \) pushing back from the gates during time period \( t \).

\( p \) = probability that the runway system is not available for take-off.

\( R(t) \) = number of pushback requests during period \( t \).

\( RQ(t) \) = number of aircraft left waiting in the departure queue on the taxiways at the end of period \( t \) (note that this queue may in some cases be spread between several departure runways).

\( T(t) \) = number of take-off during period \( t \).

\( \bar{T}_n(t) \) = "moving average" of take-off rate, i.e. the average of take-off rate over the time periods \( (t - n, \ldots, t, \ldots, t + n) \).

\( \tau_{ASQP} \) = taxi-out time recorded in the ASQP database.

\( \tau_{travel} \) = time spent traveling from the gate to the runway.

\( \tau_{queue} \) = departure runway queueing time.
# Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACARS</td>
<td>AirCraft Addressing and Reporting System</td>
</tr>
<tr>
<td>AND</td>
<td>Approximate Network Delays</td>
</tr>
<tr>
<td>APU</td>
<td>Auxiliary Power Unit</td>
</tr>
<tr>
<td>ASQP</td>
<td>Airline Service Quality Performance</td>
</tr>
<tr>
<td>CDM</td>
<td>Collaborative Decision-Making</td>
</tr>
<tr>
<td>CO</td>
<td>Carbon monoxide</td>
</tr>
<tr>
<td>CODAS</td>
<td>Consolidated Operations and Delay Analysis System</td>
</tr>
<tr>
<td>CTAS</td>
<td>Center-TRACON Automation System</td>
</tr>
<tr>
<td>DOC</td>
<td>Direct Operating Costs</td>
</tr>
<tr>
<td>DSEDM</td>
<td>Departure Sequencing Engineering and Development Model</td>
</tr>
<tr>
<td>EPA</td>
<td>Environmental Protection Agency</td>
</tr>
<tr>
<td>EPS</td>
<td>Engineering Performance Standard</td>
</tr>
<tr>
<td>ETMS</td>
<td>Enhanced Traffic Management System</td>
</tr>
<tr>
<td>FAA</td>
<td>Federal Aviation Administration</td>
</tr>
<tr>
<td>FADE</td>
<td>FAA - Airlines Data Exchange</td>
</tr>
<tr>
<td>FIMS</td>
<td>Flight Information Management System</td>
</tr>
<tr>
<td>GDP</td>
<td>Ground Delay Program</td>
</tr>
<tr>
<td>GSE</td>
<td>Ground Support Equipment</td>
</tr>
<tr>
<td>HC</td>
<td>Unburnt hydrocarbons</td>
</tr>
<tr>
<td>MPA</td>
<td>Massachusetts Port Authority</td>
</tr>
<tr>
<td>NAS</td>
<td>National Airspace System</td>
</tr>
<tr>
<td>NO\textsubscript{x}</td>
<td>Nitrogen oxides</td>
</tr>
<tr>
<td>OMS</td>
<td>Office of Mobile Sources</td>
</tr>
<tr>
<td>OAG</td>
<td>Official Airline Guide</td>
</tr>
<tr>
<td>PM</td>
<td>Particulate Matter</td>
</tr>
<tr>
<td>PRAS</td>
<td>Preferential Runway Assignment System</td>
</tr>
<tr>
<td>SO\textsubscript{x}</td>
<td>Sulfur oxides</td>
</tr>
<tr>
<td>TRACON</td>
<td>Terminal Radar Approach CONtrol</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

The continuing growth of air traffic around the world is resulting in increasing congestion and delays. Average block times between busy city pairs in the U.S. are constantly increasing (for example, the average gate-to-gate time from Boston Logan International airport to Washington National airport increased by 20% from 1973 to 1994 [1]). The major bottleneck of the U.S. National Airspace System (NAS) appears to be the airports. In less than ideal weather conditions, arrival and departure capacity can be dramatically reduced, while the airlines are often reluctant or unable to reduce the demand by cancelling flights. The reduced departure capacity can result in very long taxi-out times at peak hours, as the departing aircraft wait in a queue before being allowed to take off. These very long taxi-out times not only increase the direct operating costs for the affected flights, but also result in increased noise and pollutant emissions in the vicinity of the airports.

Therefore it is desirable to develop mechanisms to reduce these departure queues. The high financial and political costs of increasing airport capacity by adding new runways make a strong case for researching operational improvements to the existing system. This thesis develops and validates an input-output model of the current departure process at a busy airport, and uses this model to estimate the feasibility and the benefits of departure control mechanisms designed to reduce departure queues in low capacity conditions.
1.1 Modeling approach

Many relevant airport models have been developed and described in the literature. Highly detailed (or "microscopic") models such as SIMMOD or TAAM [2], reproduce the layout of an airport in great detail, and include the operating rules and dynamics of every gate, taxiway and runway for every aircraft type. These models make it possible to examine in detail the local effects of airport infrastructure or operational changes such as new terminals, new runways or new taxiways. The downside of these models is the difficulty and high cost of obtaining statistically significant validation data for all the elements of the airport under many different configurations, and to carry out an exhaustive validation from these data. It is therefore difficult and time-consuming to obtain from these models reliable estimates of the benefits of new operations concepts.

Other models, such as the Approximate Network Delays model (AND) [2] [3], take an aggregate (or "macroscopic") perspective of capacity and demand at an airport over the course of a day and provide estimates of delays. These models make it possible to study the propagation of delays at the scale of the NAS, but their macroscopic view of the airports does not capture enough detail of individual airport operations to study taxi-out time reduction schemes.

This thesis takes an intermediate modeling approach, in which input-output models of the airport terminal, taxiway and runway systems are integrated to obtain a "mesoscopic" airport model. The airport terminal system and the runway system are modeled as queueing servers, and a stochastic distribution is derived for the travel time on the taxiway system from the terminal to the runway queue. This model captures the departure process in enough detail to estimate the effectiveness of departure control schemes in reducing taxi-out times, while remaining simple enough to allow a rapid calibration and validation in each runway configuration, using readily available operational data.

A similar modeling approach was used by Shumsky to develop deterministic models which forecast take-off times of flights from major airports [4] [5]. Some of Shum-
sky’s models represent the runway system as a queueing server whose capacity is constant over 10 minute intervals. In these models, aircraft reach the runway queue at the end of a constant, deterministic travel time on the taxiway system. Shumsky also observed the relationship between airfield congestion and airport departure rate that is the basis of the simple departure control strategy evaluated in this thesis.

A mesoscopic model was also developed by Hebert [6], using five days of data, to predict departure delays at LaGuardia airport. In Hebert’s model, the departure demand is a non-homogeneous Poisson process, and taxi-out times are modeled as the sum of a nominal travel time to the runway queue and a runway service time. The runway is modeled as a multi-stage Markov process in which service completions follow an Erlang-6 distribution. The runway server can also become absent after a departure, and the absence time distribution is Erlang-9.

Analytical models of airport operations have also been proposed. Horangic mentions in his evaluation of airport modeling methods [7] that arrival runways are typically modeled as $M/E_r/k$ queueing systems $^1$ and that approximations are used for fast computations of the dynamics of such queueing systems. However, these studies focused on arrivals and ignored the departure process, for which key assumptions of the $M/E_r/k$ system (such as Poisson demand process) may not hold.

1.2 Principal contributions of the thesis

The contributions of this thesis are to provide a new model of the airport departure process that is thoroughly validated over a year of operational data, and to use this model to quantify the effects of departure process control. This work differs from earlier publications in the following manner.

- The model of the airport departure process developed in this thesis accounts for such explanatory variables as runway configurations and airline terminal location.

$^1$See reference [8] for an explanation of queueing system notations
• The model uses a stochastic representation of the travel time from the terminals to the runways, and of the departure capacity.

• In each runway configuration, the model parameters are calibrated using one year of historical data.

• In each runway configuration, the model outputs are validated using a different year of data than the one used to calibrate the model.

• Departure control schemes are proposed and tested on the departure process model. The reduction of runway queueing times achieved by these control schemes is translated into reductions in direct operating costs and pollutant emissions.

• The departure demand used to test the departure control schemes is taken from historical demand records to accurately represent "schedule bunching" (e.g. many flights are scheduled at round times for marketing reasons).

Note that the completeness and accuracy of the model are limited by the shortcomings of the data sets that were used (in particular, only jet aircraft flights are represented in the data sets). However this thesis demonstrates that the model captures the essential dynamics of the departure process, and that it can be used to estimate the benefits of departure control schemes.

1.3 Contents of the thesis

The thesis is structured as follows:

Chapter 2 introduces the ASQP and PRAS datasets that were used to validate the model and served as a baseline for the testing of new departure process control laws.

Chapter 3 describes in detail the structure of the model and the calibration / validation process.
Chapter 4 introduces a simple departure process control scheme and estimates its benefits via computer simulations.

Chapter 5 offers suggestions for future research in two areas: refinements to the model presented here, and advanced departure control schemes.

Chapter 6 summarizes the conclusions of the thesis.
Chapter 2

Data Sources

2.1 Airline Service Quality Performance (ASQP) database

The Airline Service Quality Performance (ASQP) data are collected by the Department of Transportation in order to calculate on-time performance statistics for the 10 main domestic airlines. The data sets include all the flights flown by the following airlines: Alaska, American, America West, Continental, Delta, Northwest, Southwest, TWA, United, and U.S. Airways.

For every flight recorded, the data set contains operational information such as:
- scheduled and actual gate departure times,
- actual take-off time and landing time,
- scheduled and actual gate arrival times.

ASQP data sets are made available to the public monthly (with a 2 month delay). The monthly files include around 400,000 flights. For all airlines except Southwest, the “actual” data are automatically reported through the ACARS (AirCraft Addressing and Reporting System) datalink system. For instance, the gate departure time is recorded when the brake-release ACARS message is sent by the aircraft. These data were validated by on-site observations in the case of Boston Logan airport [1]. It was found that although the brake release signal may differ slightly from the actual start
of the pushback procedure, the recorded gate departure times were very close to the pushback times observed on-site.

Actual take-off times have been made publicly available only since January 1995. Taxi-out time is defined in this thesis as the time between actual pushback and take-off. At Boston Logan airport, aircraft are constantly under the control of the Airport Control Tower between these two events, while, in the case of some larger hub airports, they are handed off from the airline ramp controllers to the Airport Control Tower at an unreported time. The departure process at an airport such as Boston Logan is thus expected to display less variability. It is also important to mention that since a single company, ARINC, receives these data in real-time, it would be relatively easy to feed them in real time into a control facility.

Note that ASQP data only take into account domestic jet operations of the ten major airlines, even though the turboprop operations of regional airlines can account for as much as 45% of the landing and take-off operations at an airport like Boston Logan [9]. It is assumed in this thesis that a useful model of the jet aircraft departure process can be identified and validated, despite the fact that the turboprops compete for the same taxiways and runways, especially in low-capacity configurations. However, the methods presented here could easily be made more accurate by considering more complete datasets as they become available. In particular, the uncertainties that were observed throughout the study of the departure process of jet aircraft could be significantly reduced if more data on turboprop operations were available.

2.2 Preferential Runway Assignment System (PRAS) database

The mix of runways that are in use at an airport at any given time is called the “runway configuration”. Consider for instance the layout of Boston Logan airport shown in Figure 2-1.

Different departure and arrival runways are used depending on weather conditions
Figure 2-1: Layout of Boston Logan International Airport
and airspace or noise abatement procedures.

- In good weather, parallel visual approaches may be used on runways 4L and 4R to achieve a high landing rate, while departures take place on runway 4R and on the intersecting runway 9 to achieve a high departure rate.

- In bad weather, and if the winds are strong, only one runway (for instance runway 33L) may be available for takeoff and landings. In such configurations, the departure and landing capacities of the airport are greatly decreased.

Figure 2-1 clearly shows that the travel time of a flight from its gate to the departure runway threshold will vary significantly with the position of the gate in the terminal and the position of the runway on the airport surface. Hence the runway configuration is likely to be an important factor in the airport taxiing operations.

Runway configurations are chosen by the airport tower controllers during the course of the day, taking into account weather condition and noise abatement objectives. Unfortunately, historical runway configuration data are usually recorded only manually in logbooks and are archived for a limited time. However, to monitor noise abatement procedures, the Massachusetts Port Authority has implemented a Preferential Runway Assignment System (PRAS) which keeps a digital log of runway configurations within the Boston Logan control tower. This thesis is focused on the operations at Boston Logan airport to take advantage of the availability of this PRAS database. However, the identification and control methods introduced in the thesis could be used at any other airports where runway configuration data would be available\(^1\).

The configurations in use at Boston Logan airport are shown in Table 2.1, along with the number of pushbacks that took place under each configuration and the approximate departure capacity (in departures/minute) used by the controllers as a benchmark [10]. Note that the airport usually operates in high-capacity configura-

\(^1\)Runway configuration data could be obtained directly from airport control tower logs, or could be inferred from recorded aircraft radar tracks.
tions (for 81% of the departure operations, the estimated departure capacity of the configuration was above 44 aircraft per hour)

However, the impact of low-capacity configurations is still important since they are associated with departure delays and very long taxi-out times. Hence, even low-capacity configurations which are not used often should be taken into account in the model, as long as enough operational samples are available to obtain statistically significant results\(^2\).

\(^2\)This thesis presents numerical results for the configurations which represented more than 1% of the flights in 1996 (i.e. more than 860 departures per year)
<table>
<thead>
<tr>
<th>No.</th>
<th>Departure runways</th>
<th>Arrival runways</th>
<th>% of 1996 pushbacks</th>
<th>Departure capacity a (aircraft / hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>33L</td>
<td>33L-33R</td>
<td>1.5</td>
<td>26</td>
</tr>
<tr>
<td>2</td>
<td>27-33L</td>
<td>33L-33R</td>
<td>15.7</td>
<td>44</td>
</tr>
<tr>
<td>3</td>
<td>4R-4L</td>
<td>4R-4L</td>
<td>2.9</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>22R-22L</td>
<td>22L-22R</td>
<td>5.3</td>
<td>34 to 44</td>
</tr>
<tr>
<td>5</td>
<td>15R-22L</td>
<td>22L-22R</td>
<td>1.6</td>
<td>34</td>
</tr>
<tr>
<td>6</td>
<td>15R</td>
<td>15R-15L</td>
<td>0.3</td>
<td>26</td>
</tr>
<tr>
<td>7</td>
<td>22R-22L</td>
<td>27 - 22L</td>
<td>31.3</td>
<td>50</td>
</tr>
<tr>
<td>8</td>
<td>9-4R-4L</td>
<td>4R-4L</td>
<td>24.4</td>
<td>50</td>
</tr>
<tr>
<td>9</td>
<td>9-4R</td>
<td>4R</td>
<td>3.9</td>
<td>34</td>
</tr>
<tr>
<td>10</td>
<td>9-4R-4L</td>
<td>4R-4L-15R</td>
<td>8.0</td>
<td>34 to 50</td>
</tr>
<tr>
<td>11</td>
<td>15R</td>
<td>4R-4L</td>
<td>1.4</td>
<td>34</td>
</tr>
<tr>
<td>12</td>
<td>4R</td>
<td>33L-33R</td>
<td>0.1</td>
<td>N/A</td>
</tr>
<tr>
<td>13</td>
<td>33L</td>
<td>15R</td>
<td>0.4</td>
<td>10</td>
</tr>
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<td>14</td>
<td>22R-22L</td>
<td>33L-33R</td>
<td>0.2</td>
<td>N/A</td>
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<tr>
<td>15</td>
<td>33L-33R</td>
<td>27</td>
<td>0.1</td>
<td>50</td>
</tr>
<tr>
<td>16</td>
<td>27-33L</td>
<td>27</td>
<td>0.2</td>
<td>50</td>
</tr>
<tr>
<td>17</td>
<td>4R</td>
<td>4R</td>
<td>0.5</td>
<td>34</td>
</tr>
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<td>9-15R</td>
<td>15R-9-15L</td>
<td>0.6</td>
<td>44</td>
</tr>
<tr>
<td>19</td>
<td>22L-22R</td>
<td>27 ADP</td>
<td>0.6</td>
<td>44 to 50</td>
</tr>
<tr>
<td>20</td>
<td>15R-9</td>
<td>15R</td>
<td>0.9</td>
<td>N/A</td>
</tr>
<tr>
<td>21</td>
<td>27-33L</td>
<td>33L-27</td>
<td>0.2</td>
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</tr>
<tr>
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<td>9-33L</td>
<td>33L-33R</td>
<td>0.02</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 2.1: Configurations at Boston Logan International Airport

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a based on airport Engineering Performance Standards, i.e. a set of standards used to determine runway capacity [10].
Chapter 3

Model Structure, Calibration and Validation

This chapter describes the departure process model that will be used in Chapter 4 to evaluate departure control schemes. Section 3.1 outlines the structure of the model. Section 3.2 explains in detail the calibration process of each element of the model, and presents comparisons of model outputs with historical data. Section 3.3 presents model validation results.

3.1 Model Structure

A schematic of the model of current departure operations is shown in Figure 3-1. The evolution of the system is modeled over discrete 1-minute time periods \( t = 1, 2, ... \) since this is how data are recorded in the ASQP and PRAS data sets.

![Figure 3-1: Structure of the departure process model for current operations.](image-url)
When an aircraft parked at a terminal is ready to depart, it calls the Airport Control Tower which delivers a pushback clearance. The aircraft is then pushed back from its gate, and it travels on the taxiways towards the departure runway. The aircraft waits for some time in the “runway queue” and then takes off. As shown in Figure 3-1, the model contains a single queueing server, which is labeled “runway queue” but is actually an aggregate representation of the queueing that takes place at various locations between the gate and the runway [11].

The model variables shown in Figure 3-1 are defined as follows:

\[ R(t) \quad = \quad \text{the number of pushback requests during period } t. \]
\[ C(t) \quad = \quad \text{the number of aircraft which are cleared to push back by the airport tower controllers during time period } t. \]
\[ P(t) \quad = \quad \text{the number of pushbacks that actually take place during period } t. \]
\[ N(t) \quad = \quad \text{the number of departing aircraft on the taxiway system (or “taxiway loading”) at the beginning of period } t. \]
\[ A(t) \quad = \quad \text{the number of aircraft reaching the runway queue during period } t. \]
\[ RQ(t) \quad = \quad \text{the number of aircraft left waiting in the departure queue on the taxiways at the end of period } t \text{ (note that this queue may in some cases be spread between several departure runways)} \]
\[ C_{dep}(t) \quad = \quad \text{the capacity of the departure runways during period } t. \]
\[ T(t) \quad = \quad \text{the number of take-offs during period } t. \]

Note that \( C_{dep}(t) \) is not the maximum theoretical capacity of the departure runway, but rather the capacity available at time \( t \) given external factors such as landings, runway crossings, etc.

The dynamics of the model are as follows:

- Airport Tower control action:

  \( C(t) \) is determined by the airport tower controllers, and can take into account:

\[ \text{[1]} \quad \text{Usually the departure runway appears to be the most limiting bottleneck between pushback and take-off, and most of the queueing takes place close to the runway threshold. In particular the departure runway is usually a more severe constraint on departure rate than the taxiways.} \]
– the current traffic conditions on the airport surface.
– the current requests $R(t)$.
– the forecasts of future departure demand and capacity.

It is assumed in this model that aircraft push back immediately after receiving their pushback clearance, so that $P(t) = C(t)$.

• Travel time:

An airplane reaches the runway queue at time $t$ if and only if it was pushed back from its gate at time $t - \tau_{\text{travel}}$, where $\tau_{\text{travel}}$ was its travel time. Hence the number $A(t)$ of airplanes that reach the runway queue at time $t$ is the sum, over all positive values of $\tau_{\text{travel}}$, of the number of airplanes which left their gates at $t - \tau_{\text{travel}}$ and had travel time $\tau_{\text{travel}}$. Therefore, the arrivals of taxiing aircraft at the runway queue $A(t)$ are related to pushbacks $P(t)$ through travel times in the following way:

$$A(t) = \sum_{\tau_{\text{travel}} \geq 0} P(t - \tau_{\text{travel}}) \left[ \sum_{k=1}^{P(t - \tau_{\text{travel}})} U(t - \tau_{\text{travel}}, k, \tau_{\text{travel}}) \right]$$

(3.1)

where $U(x, i, y)$ is an indicator random variable which takes the value 1 if the $i$-th airplane pushing back at time $x$ has travel time $y$ to the runway queue, and zero otherwise.

• Runway queue:

The runway queue satisfies the balance equation:

$$RQ(t) = RQ(t - 1) + A(t) - T(t).$$

(3.2)

• Take-off:

The achieved take-off rate is limited by the runway capacity $C_{\text{dep}}(t)$ and by the
number of aircraft available for take-off:

\[ T(t) = \min([RQ(t - 1) + A(t)], C_{dep}(t)). \]  \hspace{1cm} (3.3)

In addition, the “taxiway loading” parameter \( N(t) \) satisfies the balance equation:

\[ N(t) = N(t - 1) + P(t - 1) - T(t - 1). \]  \hspace{1cm} (3.4)

In other words, the number of departing aircraft on the taxiway system at the beginning of period \( t \) is equal to the number of departing aircraft on the taxiway system at the beginning of the previous period \( t - 1 \), plus the number of pushbacks during period \( t - 1 \), minus the number of take-offs during period \( t - 1 \).

### 3.2 Model Calibration

This section describes the process that was used to calibrate the model. The purpose of the calibration is to observe historical inputs and outputs of the systems (using the ASQP and PRAS data sets) and to deduce “best” values for the parameters of each element of the model. This section will show that observations at times when the airport traffic is light are used to calibrate the travel time element of the model, while heavy traffic observations are used to calibrate the runway capacity model parameters. Paragraphs 3.2.1 through 3.2.3 present in detail the calibration of:

- pushback requests,
- distribution of travel time from the terminals to the departure runways,
- departure runway service rate.

Paragraph 3.2.4 presents the computer simulation code that was written to implement the model and study its outputs. Paragraph 3.2.5 makes use of this computer simulation and presents a comparison of key model outputs with corresponding historical data.
3.2.1 Pushback requests and clearances

As shown in Figure 3-1, the input of the model is the number of pushback requests \( R(t) \). However this input is not captured in the ASQP data. Indeed, the Official Airline Guide (OAG) only reflects the scheduled departure times but does not account for internal airline events or decisions which could delay the request for pushback of a flight. In addition, the control action of the airport tower controllers between the requests for pushback and the pushback clearances are not observed. Consequently, the model identification presented in this thesis focuses on the motion phase of the departure process, i.e. the part of the model between \( P(t) \) and \( T(t) \). Hence, the input used for model calibration is now the number of pushbacks \( P(t) \) during period \( t \), which is the number of actual gate departures recorded during period \( t \) in the ASQP data.

Note that the actual demand profile \( P(t) \) is used as opposed to a statistical representation (such as a Poisson process) which would not replicate “schedule bunching” (i.e. the frequent scheduling of flights at round times such as 8:00, 8:15, 8:30, etc. for marketing purposes [1]).

3.2.2 Travel time from terminals to departure runway

The travel time from the terminals to the departure runway is not directly observed in the ASQP data. Indeed, the taxi-out times listed in the ASQP dataset are measured from pushback to take-off. Therefore, they represent the sum of the travel time to the runway and the time spent in the “runway queue” \(^{2} \):

\[
\tau_{ASQP} = \tau_{travel} + \tau_{queue}
\]  

(3.5)

where:

\( \tau_{ASQP} \) = taxi-out time recorded in the ASQP database;
\( \tau_{travel} \) = time spent traveling from the gate to the runway;
\( \tau_{queue} \) = runway queueing time.

\(^{2}\) Recall that in this model the “runway queue” is actually an aggregate representation of the queueing that takes place at various locations between the gates and the runway.
However, in light traffic conditions, i.e. when $N(t)$ is very low, there is usually little or no runway queue (i.e., $\tau_{\text{queue}} \approx 0$) so that equation (3.5) becomes:

$$\tau_{\text{ASQP}} \approx \tau_{\text{travel}}$$

Hence we expect the values of ASQP taxi-out times in light traffic conditions (when $N(t)$ is very low) to be a good approximation of the travel time we want to identify.

For an aircraft $k$, define $N_{PB}(k)$ to be the value of $N(t)$ when aircraft $k$ pushes back (i.e. the number of departing aircraft on the taxiway system when aircraft $k$ pushes back). Figure 3-2 shows a typical distribution of the ASQP taxi-out times $\tau_{\text{ASQP}}$ for aircraft such that $N_{PB} \leq 2$.

![Distribution of taxi-out times in light traffic](image)

**Figure 3-2**: Selection of a truncated Gaussian probability mass function to match a light traffic taxi-out distribution.
The variability in this distribution arises from several factors:

- variability in the duration of the actual pushback and the engine start;
- variability in turboprop operations of regional airlines taking place concurrently;
- different flights from the same airline can be assigned different departure runways or different taxi routes to the same runway;
- taxi speed is affected by visibility and aircraft types;
- aircraft that are bound for certain destinations may receive their weight and balance numbers later than others and thus take longer to enter the runway queue.\(^3\)

In this thesis, these factors are modeled as stochastic uncertainty. For each airline under each runway configuration, a probability mass function is fitted to the observed (or “actual”) distribution to obtain a reasonable model of travel time for low values of \(N\). This probability mass function is derived from a Gaussian probability density function of mean \(\mu\) and standard deviation \(\sigma\) in the following way:

\[
\text{for } 0 < i < \mu + 3\sigma, \quad \Pr(\tau_{\text{travel}} = i) = \frac{1}{\eta} \cdot \frac{1}{2\pi \sigma} \cdot \exp\left(-\frac{(i - 0.5 - \mu)^2}{2\sigma^2}\right),
\]

\[
\text{for } i \leq 0 \text{ or } i \geq \mu + 3\sigma, \quad \Pr(\tau_{\text{travel}} = i) = 0,
\]

where \(\eta\) is a normalization constant chosen in such a way that

\[
\sum_{i \geq 0} \Pr(\tau_{\text{travel}} = i) = 1.
\]

For instance, a probability mass function with \(\mu = 9\) minutes and \(\sigma = 2.3\) minutes was selected for the observed distribution shown in Figure 3-2. The values of \(\mu\) and \(\sigma\) for each airline in each runway configuration are given in Appendix A.

\(^3\) The weight and balance numbers of a flight take into account the passenger, cargo and fuel loads, and are used to compute essential take-off parameters. These numbers are usually determined in the Airline Operations Center and sent to the aircraft shortly before departure.
It can be seen in Figure 3-2 that the actual distribution has a long right-hand tail. This right-hand tail probably reflects:

- the runway queueing that still happens even for $N_{PB} \leq 2$,

- rare events which can delay some of the departing aircraft such as “Ground Delay Programs”.

Because of this long right-hand tail, it appears that a skewed distribution (such as an Erlang or a log-normal distribution) would fit the observed data better than a Gaussian distribution. However, since the model distribution is meant to govern the travel time (and not the runway queueing) in normal operations, its right-hand tail was made to go to zero faster than the right-hand tail of the actual distribution.\footnote{A similar procedure was used in reference [13].}

Note finally that if the travel time could be added to the list of records compiled in the ASQP database, it would allow a more precise identification of the dynamics of the departure process. This improvement may be difficult to implement however, since it would probably require a manual input from the flight crew at the time the aircraft starts queueing.

### 3.2.3 Departure runway service process

The dynamics of runway systems have been the object of numerous studies and publications. A common approach is to describe the combined departure-arrival capacity of a runway system as a time-varying pair $(\bar{C}_{dep}(t), \bar{C}_{arr}(t))$ where $\bar{C}_{dep}(t)$ is the moving average\footnote{Most studies consider averaging periods from 10 minutes to one hour.} of the departure capacity and $\bar{C}_{arr}(t)$ is the moving average of the arrival capacity during time period $t$. The maximum capacity of the runway system can then be seen as a curve or envelope in a $(d, a)$ plane, where $d$ is the departure rate and $a$ the arrival rate (e.g. in aircraft per minute) \cite{14} \cite{15}, as seen in Figure 3-3. On this capacity envelope, point $A$ corresponds to the situation in which the runway system services only arrivals, while point $D$ corresponds to the situation in which the runway
system services only departures. Points $M_1$, $M_2$ and $M_3$ correspond to various mixes of arrival and departure operations.

![Figure 3-3: Arrival and departure capacity envelope in (d,a) plane.](image)

The identification of the maximum capacity envelope can be carried out by empirical observations of airport operations [14], by analytical modeling taking into account separation constraints and other operational procedures [16], or by a combination of both.

However, discrete event departure runway models which consider each take-off individually remain difficult to identify and validate. Indeed, while there are some data available on the output of the runway system (e.g. ASQP take-off times), there are few or no objective and statistically significant data available on its inputs:

- times at which aircraft join a runway queue,
- runway crossings by taxiing or landing aircraft,
- landings on departure runways,
- landings on intersecting runways,
- take-off of turboprop aircraft.

Thus an analysis of inter-departure times cannot precisely distinguish whether a longer-than-average interval between two departures is due to a momentarily empty
runway queue or to a “server absence” (e.g. the runway being unavailable during a landing or runway crossing).

The analysis of ASQP take-off data is further complicated by the poor time resolution of the dataset: the one-minute time increments are comparable to typical runway service times.

The approach that is taken in this study is to identify periods of time when the runway queue was unlikely to be empty, and to assume that the histogram of take-off rates over these periods of time is a good approximation of the theoretical departure runway capacity distribution. This approach would be easy to implement if the runway queue length $RQ(t)$ could be directly observed. But since no runway queue length data are currently available, the number $N(t)$ of departing aircraft on the taxiway system is used instead. It will be shown here that the value of $N(t)$ is indeed a good predictor of the departure runway loading over some period of time after $t$.

Define $\bar{T}_5(t)$ to be the “moving average” of take-off rate, i.e. the average of take-off rate over the time periods $(t - n, ..., t, ..., t + n)$. Figure 3-4 illustrates the correlation between $N(t)$ and $\bar{T}_5(t)$ under configuration 8 over a time interval $(t_0, t_1)$. More specifically, it shows the value of

$$\frac{< N(t), \bar{T}_5(t + dt) >}{\|N(t)\| \cdot \|\bar{T}_5(t + dt)\|}$$

as a function of $dt$, where

$$< N(t), \bar{T}_5(t + dt) >$$

is the scalar product of the vectors $(N(t_0), ..., N(t_1))$
and $(\bar{T}_5(t_0 + dt), ..., \bar{T}_5(t_1 + dt))$,

$$\|N(t)\|$$

is the Euclidian norm of the vector $(N(t_0), ..., N(t_1))$,
and

$$\|\bar{T}_5(t + dt)\|$$

is the Euclidian norm of the vector $(\bar{T}_5(t_0 + dt), ..., \bar{T}_5(t_1 + dt))$.

The maximum correlation occurs for $dt = 6$, i.e. between $N(t)$ and $\bar{T}_5(t + 6)$. This means that $N(t)$ predicts best the number of take-offs over the time periods $(t + 1, t + 2, ..., t + 11)$. Figure 3-5 presents histograms of $\bar{T}_5(t + 6)$ for different values
Figure 3-4: Configuration 8: $N(t)$ is well correlated with $\bar{T}_5(t+6)$.
of $N(t)$ for runway configuration 8 in 1996 (departures on runways 9-4L-4R and landings on runways 4R-4L). This is a high capacity, good-weather configuration that is used often throughout the year at Boston Logan. As seen in Table 2.1, it accounted for 24.4\% of all pushbacks in 1996.

![Graph showing the evolution of $\bar{N}_5(t+6)$ as $N(t)$ varies (configuration 8).](image)

Figure 3-5: Evolution of $\bar{N}_5(t+6)$ as $N(t)$ varies (configuration 8).

As $N$ increases, the take-off rate increases at first, and then saturates as $N$ exceeds a value $N_{sat}$ (note that $N_{sat}$ depends on the runway configuration; $N_{sat} = 8$ in configuration 8)\(^6\). The highest observed departure rate is around 0.8 aircraft per minute (or 48 aircraft per hour), which is close to the Engineering Performance Standard (EPS) of 50 aircraft per hour. It corresponds to point $D$ in Figure 3-3. The saturation of the take-off rate indicates that for $N > N_{sat}$ the take-off rate is limited only by the runway capacity, and not by the runway queue becoming empty (i.e.

\(^6\) This phenomenon was described in an aggregate manner (i.e. considering all the runway configurations together) by Shumsky [4] [5].
for $N > N_{sat}$ there is enough “pressure” on the runway system to ensure that the runway system is not empty. Hence the histogram of take-off rate for $N > N_{sat}$ (i.e. for $N > 8$ in configuration 8) approximates the actual distribution of the departure capacity $\bar{C}_{dep}(t)$, and is therefore the distribution that the departure runway model will be made to replicate.

Note: the spread (or “uncertainty”) in this distribution is quite large and the mean is smaller than we would expect. For example, in configuration 8 in Figure 3-5 the standard deviation is about one third of the mean, and the mean is only 0.48 aircraft per minute (or 29 aircraft per hour), which is well below the Engineering Performance Standard of 50 aircraft per hour. This confirms that some significant explanatory factors have not been taken into account in this analysis (in particular arrivals and non-ASQP regional airline traffic). Section 5.1 explores how these additional factors could be taken into account if more data were available.

The departure runway model used in this thesis is shown in Figure 3-6.

![Figure 3-6: Probability mass function of the departure capacity of the runway system model over one minute.](image)

It is based on the “server absence” concept, which means that for each time period, there is a probability $p$ that the runway system is not available for take-off (e.g. because of a landing or a runway crossing by an arriving aircraft). If the runway system is available however, its capacity is $c$ aircraft over one time period (i.e. one minute). Paragraph 3.2.5 will demonstrate that even such a simple model
of a complex multi-runway system can reproduce quite precisely the dynamics of the departure process.

Note that in this model during each time period the runway capacity is the result of a Bernoulli trial [17] (with success if the runway system is available for take-off). Hence the average departure capacity $\bar{C}_{dep}(t)$ over the $(2n + 1)$ time periods $(t - n, ..., t, ..., t + n)$ follows the binomial distribution: for $0 \leq k \leq 2n + 1$,

$$\Pr \left( \bar{C}_{dep}(t) = k \cdot \frac{c}{2n + 1} \right) = \binom{2n + 1}{k} \cdot (1 - p)^k \cdot p^{(2n+1)-k} \quad (3.6)$$

This distribution has mean:

$$\mu = (2n + 1) \cdot (1 - p) \cdot \frac{c}{2n + 1} = (1 - p) \cdot c$$

and standard deviation:

$$\sigma = \sqrt{(2n + 1) \cdot p(1 - p) \cdot \frac{c}{2n + 1}} = c \cdot \sqrt{\frac{p(1 - p)}{2n + 1}}$$

The parameters $p$ and $c$ are chosen, for each configuration, so that the probability distribution in equation (3.6) matches the actual distribution of departure capacity $\bar{C}_{dep}$. For example, for configuration 8, Figure 3-7 and Table 3.1 show that the values $p = 0.5$ and $c = 0.97$ give an excellent match.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Model</th>
</tr>
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<tbody>
<tr>
<td>Mean</td>
<td>Std.Dev.</td>
</tr>
<tr>
<td>0.484</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Table 3.1: Actual and model statistics of departure capacity $\bar{C}_{dep}$ under configuration 8 ($p = 0.5$ and $c = 0.97$)

Appendix A shows the runway model parameters that were chosen for each runway configuration.
Figure 3-7: Actual and model distributions of departure capacity $\bar{C}_{dep}$ in configuration 8 ($p = 0.5$ and $c = 0.97$).
3.2.4 Computer implementation of the model

A computer simulation code was developed to implement the model described above. The code was written in the C programming language on a Pentium II-233Mhz personal computer running the Linux operating system. The following model parameters are stored in the computer as look-up tables:

- travel time distribution parameters for each airline in each runway configuration (see Paragraph 3.2.2);

- departure capacity distribution parameters for each runway configuration (see Paragraph 3.2.3).

The simulation code uses two input files:

- departure demand data, i.e actual pushbacks over the period of interest (e.g. the year 1996), as found in the ASQP database (see Chapter 2);

- actual runway configuration usage over the period of interest (e.g. the year 1996), as found in the PRAS database (see Chapter 2).

When the user orders a simulation run for a given runway configuration, the code simulates the departures of all the aircraft that pushed back when this runway configuration was in use. For each pushback, the travel time of the aircraft is determined by drawing a sample from the travel time distribution of the corresponding airline\(^7\). And for each time period, the departure capacity is determined by drawing a sample from the departure capacity distribution\(^7\).

During the course of the simulation run, the code stores an extensive set of model statistics and outputs, including taxiway loading, runway queueing times and take-off rates.

Since each simulation run involves randomly drawing samples from distributions, two successive simulation runs using the same inputs will give slightly different results. To reduce the impact of these fluctuations between runs, most of the simulation results shown in this thesis are averaged over ten simulation runs.

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\(^7\) A pseudo-random number generator is used to draw this sample [18].
3.2.5 Comparison of model output with historical data

The simulation code described above was used to compare key model outputs with ASQP historical data under each runway configuration. The code was given as inputs the actual 1996 departure demand data as found in the ASQP database, and the actual 1996 runway configuration usage as found in the PRAS database. All the simulation results shown in the following paragraphs were averaged over 10 simulation runs.

Since the model will be used to evaluate queueing delays and to test methods to reduce these delays, it should provide good estimates of:

- the number of aircraft that are waiting in runway queues (i.e. $RQ(t)$);
- the time these aircraft wait in runway queues (i.e. $\tau_{queue}$).

Since these values are not directly captured in the ASQP data, the model is evaluated instead on how well it predicts:

- the number of aircraft on the taxiway system when flights push back (i.e. $N_{PB}$);
- the taxi-out times $\tau$, for various values of $N_{PB}$.

The following two paragraphs provide detailed descriptions of the comparison results that were obtained for high capacity and low capacity configurations. Comparison results for each runway configuration are shown in Appendix A.

Comparison results for a high-capacity configuration

Figures 3-8, 3-9, 3-10 and Table 3.2 show comparison results for configuration number 8 (departures on runways 9 and 4R, arrivals on runways 4R and 4L). This configuration was in use for about 88200 minutes in 1996 (i.e. about 1470 hours), and represented 21500 pushbacks (which represents 24.4% of the total).

- Figure 3-8 shows the actual distribution of $N_{PB}$ that was observed in the ASQP database over 1996, along with the simulated distribution of $N_{PB}$ for the same
demand history $P(t)$. Table 3.2 presents the first two moments of the observed and simulated distributions.

![Histograms of $N_{PB}$ in configuration 8](image)

**Figure 3-8:** Actual and simulated distributions of $N_{PB}$ in configuration 8.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Std.Dev.</td>
</tr>
<tr>
<td>Mean</td>
<td>Std.Dev.</td>
</tr>
<tr>
<td>3.88</td>
<td>2.07</td>
</tr>
<tr>
<td>3.64</td>
<td>2.00</td>
</tr>
</tbody>
</table>

Table 3.2: Comparison of actual and simulated $N_{PB}$ distributions for configuration 8.

- Figure 3-9 presents the moving average of take-off rate $T_5(t+6)$ as a function of $N(t)$. The curves represent the mean of the distribution of $T_5(t+6)$ for each $N(t)$, and the vertical bars extend one standard deviation above and below the mean. The dashed lines are the observations from ASQP, while the solid

---

8 Note that the histogram shown in Figure 3-8 does not include the value $N_{PB} = 0$. This is because this value occurs very often in low traffic condition (e.g. at night and in the early morning), leading to a disproportionate amount of samples, both at the airport and in the simulation.
lines are simulation results. The fit is very good, which means that the model reproduces the relationship between departures and $N$ very well.

![Graph showing a comparison between actual and model results.]

Figure 3-9: Moving average of take-off rate $\bar{T}_5(t+6)$ as a function of $N(t)$ in configuration 8.

- Figure 3-10 presents the distribution of the taxi-out time $\tau$ for one airline, as computed from actual data and from simulation runs, over three ranges of $N_{PB}$: light traffic ($N_{PB} \leq 2$), medium traffic ($3 \leq N_{PB} \leq 7$), and heavy traffic ($N_{PB} \geq 8$).

As the traffic increases, the taxi-out time increases both in mean and in variance (this is a common occurrence in queueing systems). The model provides good fits for $N_{PB} \leq 7$ (i.e., in “light and medium traffic” conditions) but the fit is not quite as good for $N_{PB} \geq 8$ (i.e., in “heavy traffic” conditions). This might reflect the fact that as the utilization ratio\(^9\) of the departure runway system increases, small errors in the model calibration can result in large errors in queueing time estimates. Figure 3-11 illustrates this idea for a hypothetical example.

---

\(^9\) The utilization ratio is defined as the ratio of demand to capacity [8].
Figure 3-10: Taxi-out times in configuration 8.

For eight major airlines reported in the ASQP database at Boston Logan airport, the first two moments of the taxi-out time distributions were computed \(^{10}\). Almost all of the mean errors were found to be quite small (well under 10%), but some mean errors were as high as 20%. For airlines with relatively few operations, this could reflect a small sample with little statistical significance. Another explanation is that some airlines are subject to special constraints which are not included in the model (for instance, pushback and arrival operations are complex and highly coupled in an area of terminal and C called the “horseshoe” [1]).

The model tends to underestimate the standard deviation of the taxi-out distributions. This reflects the simple structure of the model, which does not fully account for some secondary factors: rare events (e.g. Ground Delay Programs), airspace constraints, differences in aircraft types, etc.

\(^{10}\) These values are given in Table A.11 in Appendix A.
Figure 3-11: Small modeling errors cause larger errors when the utilization ratio increases. In this hypothetical example, actual capacity is 60 aircraft per hour, and model capacity is 58 aircraft per hour (i.e. a 3% model calibration error was made). As demand gets close to capacity, the error in prediction of the mean queueing time increases.
Comparison results for a low-capacity configuration

Figures 3-12, 3-13, 3-14 and Table 3.3 show comparison results for configuration number 9, which is a lower capacity configuration (departures on runways 9 and 4R, and arrivals on 4R only). Configuration 9 was in use for 21800 minutes in 1996 (i.e. about 360 hours), and represented 3340 pushbacks (which represents 3.9% of the total). Since it is a low-capacity configuration used primarily in bad weather conditions, it contributes significantly to runway queueing and thus noise and pollutant emissions.

![Graph showing actual and simulated distributions of NPB in configuration 9.](image)

Figure 3-12: Actual and simulated distributions of $N_{PB}$ in configuration 9.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Std.Dev.</td>
</tr>
<tr>
<td>4.00</td>
<td>2.35</td>
</tr>
</tbody>
</table>

Table 3.3: $N_{PB}$ distributions for configuration 9.
Figure 3-12 shows the actual distributions of $N_{PB}$ over 1996 along with the simulated distributions. Table 3.3 presents the first two moments of the actual and simulated distributions.

Figure 3-13 presents the moving average of take-off rate $\bar{T}_5(t + 6)$ as a function of $N(t)$. Again the match is quite good, which means that the model reproduces very well the relationship between departures and $N$.

![Graph showing actual and model throughput](image)

Figure 3-13: Moving average of take-off rate $\bar{T}_5(t + 6)$ as a function of $N(t)$ in configuration 9.

Figure 3-14 presents the distribution of the taxi-out time $\tau$ over three ranges of $N_{PB}$.

Again, it appears that as $N_{PB}$ increases, the taxi-out time increases both in mean and in standard deviation. In this low-capacity configuration, the standard deviation in taxi-out time becomes very large for large values of $N_{PB}$ (as much as 9 minutes for a mean of 23 minutes). Possible explanations include:
Figure 3-14: Taxi-out times in configuration 9.

- transient queueing: if the demand for the departure runway temporarily exceeds the reduced departure capacity, long queues can form quickly at the runway, causing a large increase in taxi-out time.

- unmodeled weather-related factors such as Ground Delay Programs.

For eight major airlines reported in the ASQP database at Boston Logan airport, the first two moments of the taxi-out time distributions were again computed. The mean errors were found to be slightly larger than in the case of configuration 8, mostly because of the increased variability of operations under low-capacity, bad weather scenarios. In addition, the samples are about 7 times smaller than in the case of configuration 8 (because configuration 9 is not used as often) which could explain some of the higher mean errors.

\[^{11}\] These values are given in Table A.12 in Appendix A.
3.3 Model validation

Sections 3.1 and 3.2 described the calibration of the departure process model based on 1996 ASQP data. To test the applicability of this calibrated model to other years, a formal validation was performed (as defined in reference [19]). The computer simulation code described in Paragraph 3.2.4 was given as inputs the actual 1997 departure demand data as found in the ASQP database, and the actual 1997 runway configuration usage as found in the PRAS database.

The model outputs (distribution of $N_{PB}$, achieved take-off rate, and taxi-out times) were compared with the corresponding actual distributions computed from the 1997 ASQP data.

In most runway configurations the model outputs still match the actual data very closely. For configuration 4 (departures and arrivals on runways 22L and 22R) Figure 3-15 shows the distribution of $N_{PB}$ given by the model along with the actual distribution. Figure 3-16 shows the achieved take-off rates as a function of $N$, and Figure 3-17 shows the taxi-out time distributions.

![Graph](image)

Figure 3-15: Comparison of actual and simulated $N_{PB}$ distributions in configuration 4 in 1997.
Figure 3-16: Moving average of take-off rate $\bar{t}_e(t + 6)$ as a function of $N(t)$ in configuration 4 in 1997.

Figure 3-17: Taxi-out times in configuration 4 in 1997.
In some configurations however, the model slightly overestimated the departure capacity (by a factor of 5% to 10%) and consequently underestimated surface congestion and delays. This could conceivably be explained by different weather conditions or by some changes in operational procedures between 1996 and 1997. Appendix A presents model validation results for each runway configuration.
Chapter 4

Control of the Departure Process

This chapter examines the relevance, feasibility and potential benefits of departure control schemes designed to reduce departure runway queueing.

Section 4.1 introduces the two major incentives for reducing runway queueing:

- reduced Direct Operating Costs;
- reduced environmental impact.

Section 4.2 estimates the total runway queueing time over a year in current operations, and quantifies the resulting Direct Operating Costs and environmental impact.

Section 4.3 considers some of the constraints that must be taken into account in the formulation of departure process control schemes designed to reduce departure runway queueing.

Section 4.4 presents the quantitative evaluation of a simple departure process control scheme based on the "gate holding" concept. This evaluation was conducted using the model developed in Chapter 3.
4.1 Cost and environmental impact of runway queueing

4.1.1 Direct operating costs

U.S. airlines are required to report Direct Operating Costs (DOC) data to the Department of Transportation ("Form 41" [20]). Even though these data can be affected by variability in accounting methods, they provide reasonable estimates of DOC.

The major components of DOC are fuel costs, crew costs and maintenance costs. Note that marginal crew and maintenance costs are difficult to estimate because of the complex overhead costs that are associated with these components of airline operations. Estimated DOC values are shown on Table 4.1 for three different aircraft types: medium jets (e.g. Boeing 737), large jets (e.g. Boeing 757 and 767) and heavy jets (e.g. DC-10 and Boeing 747). These estimates are based on 1992 and 1995 data [21] [22] and are averaged over all major U.S. airlines.

<table>
<thead>
<tr>
<th>Jet aircraft type</th>
<th>$/min. at gate</th>
<th>$/min. in queue</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Medium</td>
<td>Large</td>
</tr>
<tr>
<td>Fuel</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Flight crew</td>
<td>2.5</td>
<td>4.5</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>2.5</td>
<td>4.5</td>
</tr>
</tbody>
</table>

Table 4.1: DOC estimates at the gate and in runway queue.

Table 4.1 shows that the DOC of each minute of runway queueing time is between $13 and $54 (depending on the aircraft type), while the DOC for a minute of delay at the gate is between $2.5 and $6. Hence a departure control scheme which would make aircraft wait at the gates rather than at the runway could achieve DOC savings of $10.5 to $48 for each minute of delay, depending on the aircraft type. Table 4.2 shows an estimate of the jet aircraft departure traffic mix at Boston Logan (this estimate was obtained from Enhanced Traffic Management System (ETMS) data collected in
June 1998) \(^1\). Combining the data in Table 4.1 and Table 4.2 yields an average cost of $3.3 per minute at the gate and $18.7 per minute in the runway queue. Hence the average DOC saving would be $15.4 for each minute of runway queueing time transferred to the gates.

<table>
<thead>
<tr>
<th>Jet aircraft type</th>
<th>% of Boston jet operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium</td>
<td>65</td>
</tr>
<tr>
<td>Large</td>
<td>30</td>
</tr>
<tr>
<td>Heavy</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 4.2: Mix of jet aircraft departure operations at Boston Logan in June 1998 (from ETMS data).

4.1.2 Environmental impact

Airports are sensitive areas in terms of pollution. The residents of nearby neighborhoods suffer from noise and pollutants generated by the airport. Among the pollutants emitted by aircraft are \([23]\) [24]:

- Nitrogen oxides \((NO_x)\), which play a role in the formation of acid rain and are precursors of particulate matter (which reduce visibility) and low-level ozone (a highly reactive gas which is a component of smog and aggravates respiratory disease).

- Unburnt hydrocarbons \((HC)\), carbon monoxide \((CO)\) and Particulate Matter \((PM)\), especially at the low engine power settings used during runway queueing.

- Sulfur oxides \((SO_x)\), which play a role in the formation of acid rain.

Note that aircraft engines typically contribute 45% of the combustion pollutants emissions at an airport, while ground access vehicles contribute another 45% and Ground Support Equipment (GSE) and Auxiliary Power Unit (APU) usage contribute only 10% \([25]\). Hence, there is a strong incentive to reduce aircraft engine emissions

\(^1\) These percentages may be somewhat biased towards high-capacity jets because the ETMS dataset also contained the international departures of U.S. carriers.
on the surface of airports. A study for the Washington state Department of Ecology estimated that departure runway queueing is responsible for a significant part of aircraft pollutant emissions at the Seattle-Tacoma airport, and in particular that it accounts for approximately 20% of \( NO_x \) emissions, 50% of \( SO_x \) emissions and 40% of \( PM \) emissions.

Table 4.3 shows engine emission characteristics for common aircraft and engine types, at the idle power setting that is typically used during runway queueing [26] [27] [28]. This table can be used to estimate the environmental impact of jets queueing on the airport taxiways. The last column shows, for each aircraft/engine combination, the percentage of jet departure operations it represented at Boston Logan in June 1998, as found in the ETMS dataset \(^2\). The last row is based on these percentages and shows the average emissions for one minute of jet aircraft runway queueing at Boston Logan airport.

<table>
<thead>
<tr>
<th>Aircraft/engine</th>
<th>Emissions (g/min)</th>
<th>% of Boston jet operations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HC</td>
<td>CO</td>
</tr>
<tr>
<td>B-757 / PW2037</td>
<td>38.24</td>
<td>390.85</td>
</tr>
<tr>
<td>MD-80 / JT8D-209</td>
<td>63.01</td>
<td>220.47</td>
</tr>
<tr>
<td>B-727 / JT8D-9A</td>
<td>74.30</td>
<td>336.73</td>
</tr>
<tr>
<td>B-737 / CFM56-3-B1</td>
<td>31.19</td>
<td>470.59</td>
</tr>
<tr>
<td>DC-9 / JT8D-9A</td>
<td>49.53</td>
<td>224.49</td>
</tr>
<tr>
<td>B-737 / JT8D-9A</td>
<td>49.53</td>
<td>224.49</td>
</tr>
<tr>
<td>A320 / V2500-A1</td>
<td>3.27</td>
<td>115.47</td>
</tr>
<tr>
<td>B-767 / CF6-80C2A2</td>
<td>237.69</td>
<td>1043.51</td>
</tr>
<tr>
<td>A300 / PW4060</td>
<td>42.43</td>
<td>519.38</td>
</tr>
<tr>
<td>B-747 / CF6-80C2A2</td>
<td>988.85</td>
<td>2803.25</td>
</tr>
<tr>
<td>DC-10 / CF6-50C</td>
<td>843.66</td>
<td>2391.66</td>
</tr>
<tr>
<td>L-1011 / RB211-R22B</td>
<td>2671.02</td>
<td>3806.93</td>
</tr>
<tr>
<td><strong>Weighted average for Boston</strong></td>
<td><strong>85.58</strong></td>
<td><strong>416.49</strong></td>
</tr>
</tbody>
</table>

Table 4.3: Jet engine aircraft emissions.

\(^2\) Again, these percentages may be somewhat biased towards high-capacity jets because the ETMS dataset also contained the international departures of U.S. carriers.
4.2 Estimation of runway queueing in current operations

Paragraph 4.2.1 presents an estimate of the current amount of runway queueing time in each airport configuration. The Direct Operating Costs (DOC) and environmental impact that are incurred as a result of this runway queueing are estimated in Paragraph 4.2.2. These costs are an upper bound on the cost savings that can be achieved by a departure control scheme.

4.2.1 Current runway queueing time

Runway queueing time is not recorded in the ASQP database. However, a computer implementation of the model developed in Chapter 3 was used to estimate the runway queueing time in ten runway configurations as shown in Table 4.4.

<table>
<thead>
<tr>
<th>Conf. number</th>
<th>% of 1996 pushbacks</th>
<th>Runway queueing (min.)</th>
<th>Runway queueing per flight</th>
<th>N_{sat}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.5</td>
<td>12,631</td>
<td>9.8</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>15.7</td>
<td>45,648</td>
<td>3.4</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>2.9</td>
<td>15,030</td>
<td>5.7</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>5.3</td>
<td>19,945</td>
<td>4.4</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>1.6</td>
<td>2,669</td>
<td>1.9</td>
<td>8</td>
</tr>
<tr>
<td>7</td>
<td>31.3</td>
<td>128,724</td>
<td>4.8</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>24.4</td>
<td>56,230</td>
<td>2.7</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>3.9</td>
<td>21,170</td>
<td>6.3</td>
<td>6</td>
</tr>
<tr>
<td>10</td>
<td>8.0</td>
<td>20,954</td>
<td>3.0</td>
<td>7</td>
</tr>
<tr>
<td>11</td>
<td>1.4</td>
<td>4,455</td>
<td>3.6</td>
<td>7</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>96.0 %</strong></td>
<td><strong>327,456 min.</strong></td>
<td><strong>4.0 min.</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4: Computer simulation estimate of runway queueing time for selected configurations at Boston Logan, using actual 1996 demand data (values are averaged over 10 simulation runs).

Note that the total amount of runway queueing time over these ten configurations

---

3 The runway configurations that are not reported in Table 4.4 were each in use for less than 1% of the 88,361 flights recorded in the ASQP dataset in 1996. Altogether they accounted for less than 4% of the flights.
was about 327,460 minutes, or 5,460 hours.

4.2.2 Direct Operating Costs and environmental impact of current runway queueing

The DOC resulting from the runway queueing times estimated above can be computed using Table 4.1. For the ten runway configurations introduced in Table 4.4, the total runway queueing DOC amount to $6,100,000 in 1996.

The runway queueing times can also be converted into pollutant emissions using Table 4.3. According to that table, the total runway queueing time of 327,460 minutes would produce:

- 28.0 tons of unburnt HC emissions,
- 136.4 tons of CO emissions,
- 22.0 tons of NO\textsubscript{x} emissions.

In order to appreciate the magnitude of these runway queue pollutant emissions, it is helpful to compare them with automobile emission figures which are made available for instance by the Office of Mobile Sources (OMS) of the United States Environmental Protection Agency (EPA) [29]. An average passenger car emits:

- 2.9 grams/mile of unburnt HC emissions,
- 22 grams/mile of CO emissions,
- 1.5 grams/mile of NO\textsubscript{x} emissions.

Hence the runway queue emissions mentioned above can be translated into the following equivalent car mileage figures:

- 28.0 tons of unburnt HC emissions $= 9.7$ million miles of HC car emissions,
- 136.4 tons of CO emissions $= 6.2$ million miles of CO car emissions,
- 22.0 tons of NO\textsubscript{x} emissions $= 14.7$ million miles of NO\textsubscript{x} car emissions.
Note that these runway queue emissions occur within the boundaries of the airport. Another useful comparison can be made by considering that a car visiting the airport from the nearby highway travels about 1.8 miles within the boundaries of the airport. The mileage figures computed above can thus be expressed as a number of car round trips in and out of the airport. Table 4.5 summarizes all the conversions.

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Runway queue emissions (per year)</th>
<th>Equivalent car miles</th>
<th>Equivalent car round trips</th>
<th>Equivalent car round trips per day</th>
</tr>
</thead>
<tbody>
<tr>
<td>$HC$</td>
<td>28.0 tons</td>
<td>9.7 million</td>
<td>5.4 million</td>
<td>14,710</td>
</tr>
<tr>
<td>$CO$</td>
<td>136.4 tons</td>
<td>6.2 million</td>
<td>3.4 million</td>
<td>9,440</td>
</tr>
<tr>
<td>$NO_x$</td>
<td>22.0 tons</td>
<td>14.7 million</td>
<td>8.2 million</td>
<td>22,330</td>
</tr>
</tbody>
</table>

Table 4.5: Conversion of runway queue emissions into equivalent car emissions.

In conclusion, the pollutant emissions due to runway queueing in the ten configurations considered here are equivalent to 9,440 to 22,330 cars visiting the airport every day of the year \(^4\). There is therefore a significant incentive to develop control schemes which would reduce runway queueing.

### 4.3 Guiding principles for control concepts

Many airport surface operations control schemes have been envisioned, but few have emphasized essential human factors considerations. Airport operations are almost entirely monitored and controlled by human operators. Workflow and workload constraints should be considered whenever the feasibility of a new airport control scheme is evaluated. Any major change to the airport control procedures would be difficult to study in-situ. Indeed, controllers are unlikely to accept any new procedures before they feel it has been proven that they not only work better than the current ones in all circumstances, but also maintain or improve safety and do not generate excessive workload or radical changes in controller roles and training.

For example, control schemes centered on sequencing should take into account the

\(^4\) As a comparison, the airport currently has 12,500 parking spaces.
fact that aircraft sequencing might require more real-time observations of the position of the aircraft on the taxiway system than are currently captured, and more interventions of the controllers to ensure the sequence is realized at the runway threshold (indeed establishing the sequence through pushback clearances alone is not enough due to large uncertainties in pushback and taxi times [1]). These additional observations and interventions entail additional workload for all airport controllers.

A departure process control experiment was conducted in the Southern California airspace in the framework of the Departure Sequencing Engineering and Development Model (DSEDM) program [30]. The objective of the program was to integrate area airports and departure airspace, and in particular to back-propagate departure fix maximum flow constraints to the airports. Departure gate holds could be used if necessary to meet these constraints. The interface between DSEDM and the airport controllers took the form of a touch-screen display in the airport control tower. This display was used to:

- update the status of a flight (e.g. clear flight to push back),
- update airport data (e.g. runway configuration),
- manipulate the flight sequence (e.g. insert a flight or swap two flights in the departure sequence).

However, experiments showed that this departure control system had too much impact on airport controller roles and workload to be accepted.

Thus it appears that the only control schemes which can bring immediate benefits are the ones which do not require changing the airport control system extensively but rather help controllers make better decisions in their current work process. The control scheme evaluated in Paragraph 4.4.2 meets this criterion. It is a simple implementation of a departure process control concept known as "gate holding".

---

5 A departure fix is a point in the airspace through which departing aircraft are routed. Aircraft separation constraints result in a “maximum flow constraint” on the the flow of aircraft through each departure fix.

6 A conceptual discussion of gate holding as a means to reduce runway queueing time recently appeared in an MIT white paper [31].
This control concept consists of holding selected departing aircraft at their gates for some time (before allowing them to pushback) if it appears that immediate pushbacks would result in long runway queues. Hence these aircraft will wait in a “gate queue” instead of the runway queue. This transfer of queueing from the runways to the gates results in reduced Direct Operating Costs and pollutant emissions.

4.4 Quantitative evaluation of a “gate holding” departure control scheme

This section examines whether the runway queueing times estimated in Section 4.2 could be reduced by a simple implementation of the “gate holding” departure control concept described above.

Paragraph 4.4.1 presents the methods and assumptions that were developed to evaluate gate holding schemes. Paragraph 4.4.2 presents the evaluation of a simple gate holding scheme based on static output feedback.

4.4.1 Evaluation method

A complete evaluation of a gate holding scheme should consider how it would interact with the current Airport Tower control actions. However, a conservative performance evaluation of such a control scheme can be obtained if it is implemented as a simple gate queue immediately downstream from the Airport Tower controllers (i.e. it is assumed that Airport Tower control actions remain the same). Figure 4-1 presents the resulting “evaluation” model.

Figure 4-1: Structure of the departure process model for control scheme evaluation.
Note that since it is assumed that the Airport Tower control actions are unaffected by the implementation of the gate queue downstream, \( C(t) \) is still simply the number of actual pushbacks recorded during period \( t \) in the ASQP data \(^7\).

Define:

\[
GQ(t) = \text{the number of aircraft which have been cleared by the airport tower controllers at or before period } t \text{ but are still being held at the gate at the end of period } t.
\]

In addition to following the equations (3.1) through (3.3) with the parameters determined in Chapter 3, the evaluation model follows the gate queue balance equation:

\[
GQ(t) = GQ(t - 1) + C(t) - P(t).
\] \hspace{1cm} (4.1)

The number \( P(t) \) of aircraft which are released from the gate queue and push back during period \( t \) is governed by the specific gate holding algorithm that is to be evaluated. Paragraph 4.4.2 and Section 5.2 present examples of such gate holding algorithms.

### 4.4.2 Evaluation of a static output feedback gate holding scheme

An easily applicable gate holding scheme can be inferred from the departure dynamics shown in Figure 3-9 and Figure 3-13 in Paragraph 3.2.3. It appears on these figures that the throughput of the runway does not improve much when \( N \) becomes larger than a saturation value \( N_{sat} \) (e.g. \( N_{sat} \approx 6 \) in configuration 9). Indeed \( N > N_{sat} \) typically corresponds to periods when the runway queue is not empty and thus when the runway is using its maximum capacity \( C_{dep}(t) \). Allowing \( N \) to become larger than \( N_{sat} \) results in more aircraft in queue at the runway with little increase in throughput. These observations suggest a control scheme (or "control law") in which aircraft are

\(^7\) It is quite possible that controllers already apply some gate holding in current operations. However, this section shows that runway queueing still occurs and could still be reduced below its current level by implementing the control scheme described in paragraph 4.4.2.
held at their gates whenever $N$ exceeds some chosen threshold value $N_c$. This amounts to controlling the number of pushbacks $P(t)$ by setting:

$$P(t) = \min( \max(N_c(t) - N(t), 0), GQ(t) - N(t)) + C(t).$$

This control scheme would be easily implemented by human controllers at an airport like Boston Logan, since $N(t)$ can be observed in the tower as the number of flight strips on the ground controller's rack.\footnote{Note that the control scheme is called a “static output feedback” scheme, following the standard control systems terminology [32], because the control decisions at time $t$ only require the observation of the current value $N(t)$ of the state variable $N$.} It could also be part of a larger scale conceptual control architecture as described in some preliminary studies [31] [33].

Figure 4-2 shows the effect of the control scheme for different values of $N_c$, under configuration 9 (for which $N_{sat} \approx 6$). It was obtained through simulation using the model shown in Figure 4-1. The simulation was run for all the time periods of 1996 when configuration 9 was in effect, using the actual departure demand found in the ASQP database but implementing the control scheme expressed by equation (4.2). The gate holding delay and runway queueing time of each flight were recorded. The total gate delay and runway queueing time over all these flights is shown in Figure 4-2.

As $N_c$ becomes smaller than $N_{sat}$ (i.e. $N_c < 6$), the runway is “starved” and the reduction in runway throughput causes an increase in total delay. But for $N_c \geq N_{sat}$ (i.e. $N_c \geq 6$), this control scheme simply replaces runway queueing time with gate delay with little impact on runway throughput. Naturally, gate delay is less costly than runway queueing time, mostly because the aircraft engines are not running while the aircraft is at the gate (see Section 4.1). Figure 4-3 shows the cumulative distributions of runway queueing time in configuration 9 for various values of $N_c$. For instance, it can be seen on this figure that the control law with parameter $N_c = N_{sat} = 6$ reduced the percentage of flights experiencing more than 10 minutes of runway queueing from 16% down to 9%.
Figure 4-2: Effect of holding aircraft at the gates when $N \geq N_c$ in configuration 9, using actual 1996 demand data (averaged over 10 simulation runs).
Figure 4-3: Cumulative distributions of runway queueing time for various values of $N_c$ in configuration 9, using actual 1996 demand data (averaged over 10 simulation runs).
Figure 4-4 shows the cumulative distributions of gate holding time in configuration 9 for the same values of $N_c$. It can be seen that more and more flights become affected by gate holding as $N_c$ is decreased (especially if it becomes lower than $N_{sat}$). However, for $N_c = N_{sat} = 6$, relatively few aircraft are affected by gate holding: only 24% are held at all, and only 11% are held for more than five minutes.

![Figure 4-4: Cumulative distributions of gate holding time for various values of $N_c$ in configuration 9, using actual 1996 demand data (averaged over 10 simulation runs).](image)

The control law was found to have similar effects in other runway configurations. Table 4.6 shows the effects of the control law on runway queueing and total queueing for the ten airport configurations introduced in Section 4.2. For each configuration, the value of the control law parameter $N_c$ was chosen in such a way that the total queueing time (i.e. the sum of the gate queueing time and the runway queueing time) would not increase by more than about 5%.

The table shows that the control law is most effective in low capacity configurations.
Table 4.6: Results of the control law for selected configurations at Boston Logan, using actual 1996 demand data (values are averaged over 10 simulation runs).

(i.e. when the demand would cause the airport to operate at values of $N$ significantly above the saturation value $N_{sat}$ if no control law were applied). The overall reduction in runway queueing time over these ten configurations is 7.8%, and the increase in total queueing time is only 3.2%. The effects on pollutant emissions are:

- 2,200 kg reduction in unburnt $HC$ emissions
- 10,700 kg reduction in $CO$ emissions
- 1,730 kg reduction in $NO_x$ emissions

As seen in Paragraph 4.2.1, these pollutant emissions can be converted into equivalent car emissions. Table 4.7 summarizes the conversions.

Table 4.7: Conversion of runway queue emissions savings into equivalent car emissions.

The net savings in Direct Operating Costs can be computed from Tables 4.1, 4.2 and 4.6 and amount to approximately $361,000.
Note that these estimates apply to 96% of the domestic jet traffic at the airport. Higher figures would be obtained if all the jet traffic was taken into account, and if the turboprop operations of regional airlines were included in the model (since they represent as much as 45% of departure operations in Boston Logan [9]). Adopting a more aggressive control law (by reducing $N_c$) would result in larger reductions in pollutant emissions (i.e. more than the 7.8% realized here), but may result in lower Direct Operating Cost savings due to the increase in total queueing time it would introduce.

Note also that if more complete operational data were available, the departure process model and control laws could be refined, and a larger part of the runway queueing pollutant emissions could be eliminated (i.e. more than the 7.8% eliminated here). There is therefore a significant incentive to obtain more data and refine departure process modeling and control laws. Section 5.1 explains in detail how additional data could be used to improve the departure process model.

The gate holding control scheme introduced in this section could have two major undesirable side effects:

- **Gate shortage**: some airlines might not have enough gate capacity at the airport to accommodate aircraft being held at the gates by the control law. This gate shortage would become more severe for lower values of the control law parameter $N_c$, as more and more aircraft would be held at the gate. Simulation runs showed that at Boston Logan in 1996, the values of $N_c$ used in Table 4.6 may not cause significant gate shortage for most airlines (the methods and assumptions used to estimate gate shortage are explained in detail in Appendix B). The last column of Table 4.8 shows how much time an airline would need one additional gate to accommodate all of its aircraft. Over these ten selected configurations which cover 96% of the 1996 traffic, an airline would on average

---

9 From a control systems perspective, the performance of the control scheme presented in this section is limited by the model uncertainty and by the delay between a control action (restricting pushbacks) and its desired effect (reducing the runway queue).
run out of gate capacity and require an additional gate only 192 minutes over
the whole year. This low figure means that, on average, the major airlines at
Boston Logan would almost always be able to accommodate the aircraft that
would be held at their gates for a short time before being cleared to push back.

- **Degraded on-time performance statistics:** the gate holding control scheme
would affect the perceived on-time performance (by delaying pushbacks) and
the actual on-time performance (by introducing some departure delay into the
system) of the airlines. Columns 5 and 6 in Table 4.8 show that for the chosen
values of the control law parameter $N_c$, on average only 2.9% of the pushbacks
would be delayed by more than 5 minutes, so that the impact on airline on-time
statistics would be quite small.

<table>
<thead>
<tr>
<th>Conf. number</th>
<th>% of 1996 pushbacks</th>
<th>$N_{\text{sat}}$</th>
<th>$N_c$</th>
<th>% flights with gate hold</th>
<th>% flights with gate hold &gt; 5 min.</th>
<th>Time 1 more gate is needed (min. over 1 year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.5</td>
<td>5</td>
<td>6</td>
<td>35.0</td>
<td>22.0</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>15.7</td>
<td>9</td>
<td>9</td>
<td>3.5</td>
<td>0.7</td>
<td>11</td>
</tr>
<tr>
<td>3</td>
<td>2.9</td>
<td>7</td>
<td>8</td>
<td>18.0</td>
<td>9.0</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>5.3</td>
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<td>8</td>
<td>8.0</td>
<td>2.8</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>1.6</td>
<td>8</td>
<td>8</td>
<td>2.0</td>
<td>0.0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>31.3</td>
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<td>7.0</td>
<td>2.7</td>
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<td>10.0</td>
<td>2.4</td>
<td>22</td>
</tr>
<tr>
<td>11</td>
<td>1.4</td>
<td>7</td>
<td>7</td>
<td>10.0</td>
<td>3.5</td>
<td>2</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>96.0 %</strong></td>
<td></td>
<td></td>
<td><strong>7.3 %</strong></td>
<td><strong>2.9 %</strong></td>
<td><strong>192 min.</strong></td>
</tr>
</tbody>
</table>

Table 4.8: Impact of the control law on on-time performance and gate shortage, for
selected configurations at Boston Logan, using actual 1996 demand data (values are
averaged over 10 simulation runs).
Chapter 5

Suggestions for future work

Section 5.1 explains why more complete datasets are needed to reduce uncertainties in the departure model presented in Chapter 3 and Chapter 4, and thus obtain more accurate model predictions.

Section 5.2 investigates how additional information on near-future departure demand and runway departure capacity could be used to provide an effective, yet easy-to-implement predictor-based departure control scheme.

5.1 Reducing uncertainties in the departure model

In Paragraph 3.2.3 it was seen that the actual departure capacity histogram (shown in Figure 3-7) has a smaller than expected mean and a large spread. Arrivals were mentioned as a possible explanation. Paragraph 5.1.1 explains how the effects of arrivals on departure capacity could be detected in the data. Paragraph 5.1.2 shows that the ASQP dataset is not complete enough to detect these arrival-departure interaction effects and concludes that more complete datasets are needed to reduce uncertainties in the departure model.
5.1.1 Expected effects of arrivals on departure model uncertainty

Define:
\[ \bar{L}_5(t) = \text{the moving average of the arrival (or "landing") rate over} \]
\[ \text{the time periods } (t + 1, t + 2, ..., t + 11) \]

Arrivals can decrease the runway departure capacity when arrival and departure operations are not independent. For instance, if the runway system had the hypothetical capacity envelope\(^1\) shown in Figure 5-1 and if the moving average of arrival rate \( \bar{L}_5(t) \) were distributed as shown on the left side of the figure, the distribution of the moving average of departure capacity \( \bar{C}_{dep}(t) \) (shown at the bottom of the figure) would closely match the actual distribution observed in Figure 3-7.

![Figure 5-1: Effect of arrival rate distribution on \( Pr(\bar{L}_5(t) = a) \) on departure capacity distribution \( Pr(\bar{C}_{dep}(t) = d) \).](image)

A simple test of the correlation between arrival rate and departure capacity is to plot in the \((d,a)\) plane the observed joint probability distribution of \( \bar{C}_{dep}(t) \) and \( \bar{L}_5(t) \), i.e. \( Pr(\bar{C}_{dep}(t) = d \text{ and } \bar{L}_5(t) = a) \). If arrivals were indeed the major factor in the spread of the departure capacity distribution, then this joint probability distribution

\(^1\) See Paragraph 3.2.3
would be very narrow and would follow the capacity envelope closely, as shown in Figure 5-2.

![Figure 5-2: Hypothetical joint probability distribution of C_{dep}(t) and L_5(t) Darker shades of grey indicate higher probability densities.](image)

Then for each value of the landing rate (\( \bar{L}_5(t) = a_1, a_2, \text{etc.} \)) the marginal distributions of departure capacity (\( \Pr(\bar{C}_{dep}(t) = d \mid \bar{L}_5(t) = a_1), \Pr(\bar{C}_{dep}(t) = d \mid \bar{L}_5(t) = a_2), \text{etc.} \)) would have a smaller spread, as illustrated in Figure 5-3. In other words, if the arrival rate and departure capacity were indeed strongly correlated, the conditional distribution \( \Pr(\bar{C}_{dep}(t) = d \mid \bar{L}_5(t) = a) \) would have a smaller uncertainty than the a-priori distribution \( \Pr(\bar{C}_{dep}(t) = d) \).

This in turn would mean that the departure runway model parameters \( p \) and \( c \) (described in Paragraph 3.2.3) should be time-varying and should depend on the arrival rate:

\[
p(t) = f_p(\bar{L}_5(t)),
\]

\[
c(t) = f_c(\bar{L}_5(t)).
\]
Figure 5-3: The marginal departure capacity distribution \( \Pr(\tilde{C}_{dep}(t) = d \mid \tilde{L}_5(t) = a) \) would have a smaller spread than the a-priori distribution \( \Pr(\tilde{C}_{dep}(t) = d) \) for each value \( a \) of the arrival rate.
5.1.2 Arrival-departure interactions in the ASQP dataset

Figure 5-4 and Figure 5-5 show the joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ in the $(d,a)$ plane for $N(t) > N_{sat}$ in configuration 1 and 8 respectively\textsuperscript{2}, as computed from the ASQP data set\textsuperscript{3}. Note that configuration 1 is a single-runway configuration in which departing and arriving aircraft share runway 33L. We would expect a strong correlation between arrival rate and departure capacity in this configuration.

![Joint probability distribution](image)

Figure 5-4: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$ in configuration 1.

It can be seen however that the observed distributions in Figure 5-4 and Figure 5-5 do not closely resemble the hypothetical distribution shown in Figure 5-2.\textsuperscript{4} In particular, for a given value of the arrival rate, the marginal departure capacity distribution $\Pr(\bar{C}_{dep}(t) = d \mid \bar{L}_5(t) = a)$ does not have a smaller spread than the a-priori distribution $\Pr(\bar{C}_{dep}(t) = d)$. In other words, knowing the arrival rate of jet aircraft is not enough to reduce the uncertainty of the departure capacity estimate. In addition, in several configurations the average departure rate in the ASQP data set

\textsuperscript{2} Recall that we consider $\bar{T}_5(t + 6)$ for $N(t) > N_{sat}$ to be a good approximation of $\bar{C}_{dep}(t)$.

\textsuperscript{3} Recall that the ASQP data set only contains records of the jet aircraft operations of the ten major airlines.

\textsuperscript{4} Appendix A shows that this is also the case for several other runway configurations.
Figure 5-5: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$ in configuration 8.

does not depend significantly on the arrival rate (e.g. the crosses in Figure 5-4 and Figure 5-5 form a quasi-vertical line as opposed to the expected downward sloping line).

These observations are unexpected because it is well documented that the arrival and departure capacities of an airport are not independent. They can be tentatively explained by the other major factor that was not taken explicitly into account in this thesis: regional airline flights which use part of the available departure capacity but are not recorded in the ASQP dataset. More complete datasets which include all of the airport traffic (e.g. the Consolidated Operations and Delay Analysis System or “CODAS” data [34]) could be used to reduce the uncertainty in departure capacity distributions and thus obtain a better departure runway model.
5.2 Implementing predictor-based control schemes

The control scheme described in Paragraph 4.4.2 relies exclusively on the observation of the current state of the airport (in particular $N(t)$, the number of departing aircraft on the taxiway system). It takes into account neither the future departure demand, nor the future evolution of runway departure capacity (e.g. due to predictable changes in the arrival rate). A control scheme which used estimates of future departure demand and runway capacity in addition to the current state of the airport should achieve an additional reduction in runway queueing times.

Paragraphs 5.2.1 and 5.2.2 consider the availability of data on future departure demand and runway capacity. Paragraph 5.2.3 presents a control scheme architecture, based on departure slot allocation, which would take advantage of these data. Paragraph 5.2.4 presents initial results obtained by applying a simple departure slot allocation algorithm to Boston Logan.

5.2.1 Departure demand information

In current operations, the only future departure demand information available to the Air Traffic Control Tower is the Flight Information Management System (FIMS) maintained by the airlines to inform their passengers of planned departure times. FIMS is not always accurate since it does not instantly reflect some sources of potential departure delays:

- late inbound resources (aircraft, crew, flight attendants),
- departure holds to allow late passenger connections,
- delays in preparing the aircraft for departure (passenger boarding, baggage and cargo loading, catering, etc.),
- aircraft mechanical problems currently under investigation ("flights on decision").
FIMS is however a good indication of future demand on a short time scale.

It can be envisioned that more departure demand information will become available in the future. Indeed, since the early days of the FAA - Airlines Data Exchange (FADE) program, significant progress has been made in the definition and implementation of Collaborative Decision-Making (CDM) procedures, which allow the airlines and the FAA to exchange more accurate information on future departure demand in the context of Ground Delay Programs (GDP). Such information could be used to predict departure demand more accurately on longer time scales ⁵.

5.2.2 Runway capacity information

The departure capacity of a runway system can be directly affected by many factors, including:
- weather conditions,
- departure airspace constraints,
- arrivals.

The weather conditions can usually be forecast with satisfactory accuracy 30 minutes in advance (one possible exception is drifting fog conditions). Airspace constraints also vary slowly and are quite predictable.

In current operations however, the future arrivals at an airport are not known with good accuracy, due to uncertainties in the timing of aircraft descent profiles and approach paths. The new Center-TRACON Automation System (CTAS) has been shown to improve the accuracy of arrival time predictions significantly [35] [36]. It appears possible to predict future arrivals up to 15 minutes in advance with an accuracy of 30 seconds.

⁵ Note however that future departure times are not always known even within the Airline Operating Centers, due to uncertainties in aircraft and crew availability
5.2.3 Slot allocation architecture

The concept of landing slot allocation is used extensively at major congested airports such as Chicago O'Hare and London Heathrow, and also at smaller airports during Ground Delay Programs. The same concept can be applied to departure operations. However, a strict application of the concept would require airport tower controllers to actively control taxiing aircraft to ensure that they arrive in the correct order and at the correct times to comply with the slot allocation. This would make the testing and implementation of the concept difficult and costly. In order to minimize disruptions to the current controller work processes, the slot allocation process could be limited to determining optimal pushback times. Aircraft would be held at the gate until a desired pushback time which should take them to the runway in time for their take-off slot. After pushback, controllers would not be required to ensure that aircraft are exactly complying with the slot allocation. The price to pay for this simplicity is an increased vulnerability to uncertainties in taxi times.

Define $H$ to be the time horizon for predictions and slot allocations. Based on Paragraphs 5.2.1 and 5.2.2, a reasonable value for $H$ would be 20 minutes. A simple departure slot control architecture could be used to implement the concept:

- **Step 1a.** Prediction of departure runway capacity: the future departure runway capacity is predicted over $(t, t + H)$ taking into account weather, airspace constraints, arrivals, etc. as outlined in Paragraph 5.2.1

- **Step 1b.** Prediction of runway arrival times: the times at which currently taxiing aircraft will arrive at the runway are estimated, and the remaining departure runway capacity is computed.

- **Step 1c.** Prediction of departure demand: based on the published schedule and updates from the airline control centers, a "departure pool" consisting of the aircraft which will request a departure over $(t, t + H)$ is estimated.

- **Step 2.** Take-off slot allocation: an algorithm allocates the available departure runway capacity to aircraft in the departure pool. The algorithm should try to
minimize runway queueing times while respecting some key constraints (e.g. in general, an aircraft cannot leave its gate before its published departure time) and fairness rules (e.g. first come first served).

- **Step 3. Selection of pushback times:** a pushback time is selected for each aircraft in the departure pool which has been assigned a slot, taking into account the time it will take for the aircraft to reach the runway under current airport conditions.

**Notes:**

- the slot allocation algorithm should take into account the uncertainty arising in the runway departure capacity and demand predictions.

- the selected pushback times should also take into account the uncertainty in the travel time to the runway.

- the control points in the departure process are currently the object of more detailed studies [33].

### 5.2.4 Slot allocation algorithm

Many algorithms (or combinations thereof) can be used to optimize the slot allocation process, including:

- heuristics,

- static mathematical programming [37],

- Dynamic Programming (DP) or Approximate Dynamic Programming [38].

A simple heuristic was used to obtain a conservative estimate of potential benefits of the departure slot allocation concept. This heuristic is an implementation of the architecture described in Paragraph 5.2.3.

- **Step 1a:** the predicted departure runway capacity is taken to be constant over \((t, t + H)\) and equal to the average capacity observed in this configuration under high taxiway loading (e.g. under configuration 9, Figure 3-13 shows that the average departure capacity under high taxiway loading is around 0.35 aircraft/minute).
• Step 1b: the runway arrival time of each taxing aircraft is estimated by adding to its pushback time the average travel time for its airline in this particular runway configuration (see Paragraph 3.2.2).

• Step 1c: future departure requests are assumed to be known exactly over \((t, t + H)\).

• Step 2. The slot allocation algorithm spreads the departure demand to ensure that the predicted runway queue over \((t, t + H)\) does not exceed a target runway buffer \(RQ_c\). Slots are allocated according to the following variation of the first come first served rule: out of all the aircraft in the departure pool which could be assigned to a take-off slot, the aircraft that is actually assigned is the one with the earliest departure request time.

In initial computer simulation tests, the heuristic departure slot allocation algorithm described above did not perform as well as the simple static output feedback gate holding scheme introduced in Paragraph 4.4.2.

The relatively poor performance of the predictor-based algorithm can be attributed to the large uncertainties in travel times and departure capacity. The introduction of additional airport operations data into the model (such as arrivals and turboprop operations) should reduce these uncertainties (as explained in Section 5.1) and improve the performance of slot allocation algorithms.
Chapter 6

Conclusion

The experimental investigation related in this thesis has addressed the problem of modeling the departure process at a busy airport in order to alleviate surface congestion. This investigation relied on ASQP and other available datasets to develop a simple, yet extensively validated dynamical queueing model of the departure process. A computer implementation of this model has shown that active control strategies can use aircraft gate holding to reduce congestion on the airport surface. These strategies achieve a reduction in direct operating costs and environmental costs without increasing total delay significantly. Their implementation would be compatible with the current airport operations and human-in-the-loop control structure. Further research could combine aircraft departure control with arrival control, with the intent to improve overall airport efficiency. Further efficiency could also be gained by reducing model uncertainties as more complete datasets become available, and by investigating more advanced control laws.
Appendix A

Boston Logan airport model calibration / validation results

A.1 Synopsis for each runway configuration

This section summarizes the main results of the model calibration and validation. For each configuration, the following results are shown:

- travel time and runway model parameters (see Paragraphs 3.2.2 and 3.2.3);
- comparison of 1996 historical data and computer simulation outputs (see Paragraph 3.2.5)
  - distribution of $N_{PB}$;
  - $T_5(t + 6)$ as a function of $N(t)$;
- validation plots, i.e. comparison of 1997 historical data and computer simulation outputs (see Section 3.3)
  - distribution of $N_{PB}$;
  - $T_5(t + 6)$ as a function of $N(t)$;
- joint probability distribution of take-off rate $T_5(t + 6)$ and landing rate $L_5(t + 6)$ for $N > N_{sat}$ (see Paragraph 5.1.2).
Configuration 1 (dep. & arr. on runway 33L)

Figure A-1: Selection of travel time distribution for airline number 8.

<table>
<thead>
<tr>
<th>Airline</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>10.5</td>
<td>14.0</td>
<td>12.5</td>
<td>11.7</td>
<td>14.5</td>
<td>14.0</td>
<td>10.7</td>
<td>12.2</td>
<td>11</td>
</tr>
<tr>
<td>$\sigma$</td>
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<td>2.5</td>
<td>3.0</td>
<td>2.0</td>
<td>1.5</td>
<td>2.0</td>
<td>2.7</td>
<td>2.0</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Table A.1: Travel time distribution parameters

Departure runway service parameters: $p = 0.62$ $c = 0.82$

Figure A-2: Actual and model distributions of $N_{PB}$ in 1996.

Figure A-3: Take-off rate $\bar{T}_5(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-4: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-5: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-6: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{Sat}$.
Configuration 2 (dep. 27-33L, arr. 33L-33R)

![Graph showing distribution of travel time for airline number 9.](image)

Figure A-7: Selection of travel time distribution for airline number 9.

<table>
<thead>
<tr>
<th>Airline</th>
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<th>3</th>
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<tr>
<td>$\sigma$</td>
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<td>2.2</td>
<td>2.0</td>
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<td>1.8</td>
<td>2.1</td>
<td>2.0</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Table A.2: Travel time distribution parameters

Departure runway service parameters: $p = 0.50$  $c = 0.91$

![Histograms of $N_{PB}$ in configuration 2](image)

Figure A-8: Actual and model distributions of $N_{PB}$ in 1996.

![Graph showing take-off rate $\dot{T}_5(t + 6)$ as a function of $N(t)$ in 1996.](image)

Figure A-9: Take-off rate $\dot{T}_5(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-10: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-11: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-12: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$. 
Configuration 3 (dep. 4R-4L, arr. 4R-4L)

![Distribution of two-out times in light traffic](image)

Figure A-13: Selection of travel time distribution for airline number 3.

<table>
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<td>8.8</td>
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<td>15.3</td>
<td>13</td>
<td>13.6</td>
<td>9.8</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>2</td>
<td>2.6</td>
<td>2.8</td>
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<td>2</td>
<td>2.4</td>
<td>1.5</td>
<td>2.6</td>
<td>1.8</td>
</tr>
</tbody>
</table>

Table A.3: Travel time distribution parameters

Departure runway service parameters: $p = 0.61 \quad c = 1.0$

![Actual vs. Model](image)

Figure A-14: Actual and model distributions of $N_{PB}$ in 1996.

![Actual vs. Model](image)

Figure A-15: Take-off rate $\tilde{T}_5(t + 6)$ as a function of $N(t)$ in 1996.

89
Figure A-16: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-17: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-18: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$. 
Configuration 4 (dep. & arr. 22L-22R)

Figure A-19: Selection of travel time distribution for airline number 8.

<table>
<thead>
<tr>
<th>Airline</th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tbody>
<tr>
<td>$\mu$</td>
<td>11.0</td>
<td>14.3</td>
<td>10.6</td>
<td>11.2</td>
<td>11.7</td>
<td>11.1</td>
<td>9.6</td>
<td>12.5</td>
<td>11.5</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
<td>2.2</td>
<td>1.5</td>
<td>1.7</td>
<td>1.7</td>
<td>1.8</td>
<td>1.8</td>
</tr>
</tbody>
</table>

Table A.4: Travel time distribution parameters

Departure runway service parameters: $p = 0.59 \quad c = 0.91$

Figure A-20: Actual and model distributions of $N_{PB}$ in 1996.

Figure A-21: Take-off rate $\hat{T}_5(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-22: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-23: Validation: take-off rate $\bar{T}_5(t+6)$ vs $N(t)$ in 1997.

Figure A-24: Joint probability distribution of $\bar{T}_5(t+6)$ and $\bar{L}_5(t+6)$ for $N > N_{sat}$.
Configuration 5 (dep. 15R-22L, arr. 22R-22L)

Figure A-25: Selection of travel time distribution for airline number 1.

<table>
<thead>
<tr>
<th>Airline</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<th>9</th>
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</thead>
<tbody>
<tr>
<td>(\mu)</td>
<td>11.4</td>
<td>16</td>
<td>10.6</td>
<td>11.2</td>
<td>11.7</td>
<td>10.9</td>
<td>9.4</td>
<td>11.9</td>
<td>11.8</td>
</tr>
<tr>
<td>(\sigma)</td>
<td>2</td>
<td>2.5</td>
<td>2</td>
<td>2.2</td>
<td>1.5</td>
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</tbody>
</table>

Table A.5: Travel time distribution parameters

Departure runway service parameters: \(p = 0.50\) \(c = 1.0\)

Figure A-26: Actual and model distributions of \(N_{PB}\) in 1996.

Figure A-27: Take-off rate \(\hat{T}_5(t+6)\) as a function of \(N(t)\) in 1996.
Figure A-28: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-29: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-30: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$. 
Configuration 7 (dep. 22L-22R, arr. 22L-27)

Figure A-31: Selection of travel time distribution for airline number 4.

<table>
<thead>
<tr>
<th>Airline</th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>$\mu$</td>
<td>11.5</td>
<td>14.3</td>
<td>10.5</td>
<td>10.6</td>
<td>14</td>
<td>10.7</td>
<td>9.7</td>
<td>12.4</td>
<td>12.2</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>2.0</td>
<td>2.3</td>
<td>1.9</td>
<td>1.9</td>
<td>3.0</td>
<td>1.8</td>
<td>1.6</td>
<td>1.8</td>
<td>1.9</td>
</tr>
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</table>

Table A.6: Travel time distribution parameters

Departure runway service parameters: $p = 0.56$  $c = 0.91$

Figure A-32: Actual and model distributions of $N_{PB}$ in 1996.

Figure A-33: Take-off rate $\dot{T}_S(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-34: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-35: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-36: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$. 
Configuration 8 (dep. 9-4L-4R, arr. 4L-4R)

![Distribution of time-out time in high traffic](image)

Figure A-37: Selection of travel time distribution for airline number 9.

<table>
<thead>
<tr>
<th>Airline</th>
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<th>3</th>
<th>4</th>
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<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\mu)</td>
<td>9.9</td>
<td>10.8</td>
<td>10.5</td>
<td>7.5</td>
<td>10</td>
<td>12.2</td>
<td>11.7</td>
<td>11.4</td>
<td>8.4</td>
</tr>
<tr>
<td>(\sigma)</td>
<td>2.4</td>
<td>2.2</td>
<td>2.1</td>
<td>2.0</td>
<td>2.7</td>
<td>2.2</td>
<td>2.2</td>
<td>1.8</td>
<td>1.8</td>
</tr>
</tbody>
</table>

Table A-7: Travel time distribution parameters

Departure runway service parameters: \(p = 0.5\) \(c = 1.0\)

![Histogram of \(N_{PB}\) in configuration 8](image)

Figure A-38: Actual and model distributions of \(N_{PB}\) in 1996.

![Graph of \(\hat{T}_5(t + 6)\) as a function of \(N(t)\) in 1996](image)

Figure A-39: Take-off rate \(\hat{T}_5(t + 6)\) as a function of \(N(t)\) in 1996.
Figure A-40: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-41: Validation: take-off rate $T_5(t+6)$ vs $N(t)$ in 1997.

Figure A-42: Joint probability distribution of $T_5(t+6)$ and $L_5(t+6)$ for $N > N_{sat}$.
Configuration 9 (dep. 9-4R, arr. 4R)

![Distribution of time-in-use in flight traffic](image1)

Figure A-43: Selection of travel time distribution for airline number 4.

<table>
<thead>
<tr>
<th>Airline</th>
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<th>2</th>
<th>3</th>
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<th>5</th>
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<td>10.2</td>
<td>11.5</td>
<td>11.4</td>
<td>11.4</td>
<td>8.3</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>3.6</td>
<td>3.0</td>
<td>3.4</td>
<td>2.0</td>
<td>2.5</td>
<td>2.3</td>
<td>2.6</td>
<td>2.3</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Table A.8: Travel time distribution parameters

Departure runway service parameters: $p = 0.62$ \( c = 0.91 \)

![Actual vs Model](image2)

Figure A-44: Actual and model distributions of $N_{PB}$ in 1996.

![Actual vs Model](image3)

Figure A-45: Take-off rate $\tilde{T}_5(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-46: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-47: Validation: take-off rate $T_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-48: Joint probability distribution of $T_5(t + 6)$ and $L_5(t + 6)$ for $N > N_{sat}$. 
Configuration 10 (dep. 9-4R-4L, arr. 4R-4L-15R)

Figure A-49: Selection of travel time distribution for airline number 9.

<table>
<thead>
<tr>
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<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>$\mu$</td>
<td>9.9</td>
<td>10.8</td>
<td>11.3</td>
<td>8</td>
<td>10</td>
<td>12.2</td>
<td>12.7</td>
<td>11.4</td>
<td>8.6</td>
</tr>
<tr>
<td>$\sigma$</td>
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<td>2.5</td>
<td>2</td>
<td>2</td>
<td>2.2</td>
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</tbody>
</table>

Table A.9: Travel time distribution parameters

Departure runway service parameters: $p = 0.46$ $c = 0.91$

Figure A-50: Actual and model distributions of $N_{PB}$ in 1996.

Figure A-51: Take-off rate $\bar{T}_5(t+6)$ as a function of $N(t)$ in 1996.
Figure A-52: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-53: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-54: Joint probability distribution of $T_5(t + 6)$ and $L_5(t + 6)$ for $N > N_{sat}$. 
Configuration 11 (dep. 15R, arr. 4R-4L)

![Graph](image)

Figure A-55: Selection of travel time distribution for airline number 9.

<table>
<thead>
<tr>
<th>Airline</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<th>9</th>
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<td>11.5</td>
<td>10.8</td>
<td>9</td>
<td>12.2</td>
<td>12.2</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.8</td>
<td>1.8</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2.7</td>
<td>2.7</td>
<td>3</td>
<td>3</td>
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</tbody>
</table>

Table A.10: Travel time distribution parameters

Departure runway service parameters: $p = 0.5 \quad c = 0.82$

![Graph](image)

Figure A-56: Actual and model distributions of $N_{PB}$ in 1996.

![Graph](image)

Figure A-57: Take-off rate $\hat{T}_5(t + 6)$ as a function of $N(t)$ in 1996.
Figure A-58: Validation: actual and model distributions of $N_{PB}$ in 1997.

Figure A-59: Validation: take-off rate $\bar{T}_5(t + 6)$ vs $N(t)$ in 1997.

Figure A-60: Joint probability distribution of $\bar{T}_5(t + 6)$ and $\bar{L}_5(t + 6)$ for $N > N_{sat}$. 
A.11 Comparison of the first two moments of actual and modeled taxi-out distributions

For eight major airlines reported in the ASQP database at Boston Logan airport \(^1\), the first two moments of the actual and simulated taxi-out time distributions were computed. The results are reported in Table A.11 and Table A.12.

\(^1\) Airline #5 had very few flights and is not included here.
### Light traffic ($N_{PB} \leq 2$)

<table>
<thead>
<tr>
<th>Airline</th>
<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.01</td>
<td>5.08</td>
<td>11.95</td>
<td>3.25</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>12.97</td>
<td>4.12</td>
<td>12.89</td>
<td>3.08</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>12.76</td>
<td>3.81</td>
<td>12.54</td>
<td>2.94</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>9.33</td>
<td>3.01</td>
<td>9.48</td>
<td>2.77</td>
<td>-2</td>
</tr>
<tr>
<td>6</td>
<td>14.37</td>
<td>3.83</td>
<td>14.27</td>
<td>3.11</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>14.16</td>
<td>4.12</td>
<td>13.94</td>
<td>3.21</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>13.66</td>
<td>4.41</td>
<td>13.44</td>
<td>2.76</td>
<td>2</td>
</tr>
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<td>9</td>
<td>10.26</td>
<td>3.27</td>
<td>10.38</td>
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### Medium traffic ($3 \leq N_{PB} \leq 7$)

<table>
<thead>
<tr>
<th>Airline</th>
<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
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<tr>
<td>1</td>
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<td>5</td>
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<tr>
<td>3</td>
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<td>3.6</td>
<td>7</td>
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<tr>
<td>4</td>
<td>11.21</td>
<td>4.55</td>
<td>11.09</td>
<td>3.91</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>15.94</td>
<td>4.69</td>
<td>15.29</td>
<td>3.56</td>
<td>4</td>
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<td>7</td>
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<td>5.71</td>
<td>14.95</td>
<td>3.63</td>
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<td>12.36</td>
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</table>

### Heavy traffic ($N_{PB} \geq 8$)

<table>
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<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
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</thead>
<tbody>
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<td>18.9</td>
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<td>5.6</td>
<td>-2</td>
</tr>
<tr>
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<td>19.18</td>
<td>6.87</td>
<td>19.82</td>
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<td>18.82</td>
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<td>19.79</td>
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<td>-5</td>
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<td>14.12</td>
<td>5.14</td>
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<td>5.54</td>
<td>-20</td>
</tr>
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<td>19.26</td>
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<td>21.2</td>
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<td>-10</td>
</tr>
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<td>5.44</td>
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</table>

Table A.11: First two moments of taxi-out distributions in light, medium and heavy traffic in configuration 8
### Light traffic ($N_{PB} \leq 2$)

<table>
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<tr>
<th>Airline</th>
<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
</tr>
</thead>
<tbody>
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<td>7.27</td>
<td>13.17</td>
<td>4.33</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
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<td>5.17</td>
<td>13.05</td>
<td>3.98</td>
<td>7</td>
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<td>14.32</td>
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<td>13.84</td>
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<tr>
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<td>14.06</td>
<td>3.44</td>
<td>14</td>
<td>3.54</td>
<td>0</td>
</tr>
<tr>
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<td>11.67</td>
<td>5.18</td>
<td>10.91</td>
<td>3.29</td>
<td>7</td>
</tr>
</tbody>
</table>

### Medium traffic ($3 \leq N_{PB} \leq 7$)

<table>
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<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
</tr>
</thead>
<tbody>
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<td>6.04</td>
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</tr>
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<tr>
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<td>16.24</td>
<td>5.41</td>
<td>16.97</td>
<td>5.24</td>
<td>-4</td>
</tr>
<tr>
<td>9</td>
<td>14.73</td>
<td>7.41</td>
<td>14.25</td>
<td>5.43</td>
<td>3</td>
</tr>
</tbody>
</table>

### Heavy traffic ($N_{PB} \geq 8$)

<table>
<thead>
<tr>
<th>Airline</th>
<th>Actual mean</th>
<th>Actual $\sigma$</th>
<th>Model mean</th>
<th>Model $\sigma$</th>
<th>Mean error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20.42</td>
<td>4.85</td>
<td>26.67</td>
<td>7.43</td>
<td>-31</td>
</tr>
<tr>
<td>2</td>
<td>25.41</td>
<td>7.99</td>
<td>26.61</td>
<td>7.35</td>
<td>-5</td>
</tr>
<tr>
<td>3</td>
<td>22.67</td>
<td>9.23</td>
<td>26.89</td>
<td>7.04</td>
<td>-19</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>21.8</td>
<td>5.23</td>
<td>27.12</td>
<td>6.29</td>
<td>-24</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>21.32</td>
<td>6.05</td>
<td>27.55</td>
<td>6.99</td>
<td>-29</td>
</tr>
<tr>
<td>9</td>
<td>26.14</td>
<td>8.98</td>
<td>24.88</td>
<td>7.07</td>
<td>5</td>
</tr>
</tbody>
</table>

Table A.12: First two moments of taxi-out distributions in light, medium and heavy traffic in configuration 9
Appendix B

Accounting methods for gate utilization and gate shortage estimations

B.1 Definition of gate capacity

Estimating the number of jet aircraft that an airline can park at an airport is not as straightforward as it may seem. The number of gates that each airline reportedly owns or rents at the airport is variable and is not always an exact reflection of how many jet aircraft the airline can actually accommodate:

- The size and geometry of the gate areas might restrict the type of aircraft that can be parked at each gate. Moreover, parking a wide-body jet at one gate can in some cases forbid the use of a neighboring gate.

- A gate that is reportedly used by an airline can be sub-leased to another airline (e.g. a regional airline partner).

- At some airports, airlines use ramp and hangar spaces extensively to complement the gate space, thus increasing the number of aircraft that they can
accommodate at any time\(^1\).

The ASQP dataset makes it possible to estimate how many aircraft each airline is keeping on the ground at any time. However, it does not differentiate between aircraft being kept at the gates and aircraft parked on the ramp or in hangar spaces. Hence we define, for each airline in the ASQP dataset, the "gate capacity" to be:

\[
G_i = \text{maximum number of jet aircraft that airline } i \text{ can accommodate at any time.}
\]

Considering gate and hangar space together is a simplification because moving aircraft to and from ramp or hangar spaces costs the airlines more time and manpower than only using gates.

### B.2 Observations of gate usage in the ASQP database

Since the ASQP database records pushbacks and gate arrivals, it is in theory possible to know at all times how many jet aircraft each airline has parked.

Define:

\[
g_i(t) = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of time period } t.
\]

\[
A_i(t) = \text{number of jet aircraft of airline } i \text{ arriving at the gates during time period } t.
\]

\[
P_i(t) = \text{number of jet aircraft of airline } i \text{ pushing back from the gates during time period } t.
\]

Then \(g_i(t)\) obeys the following balance equation:

\[
g_i(t) = g_i(t - 1) + A_i(t - 1) - P_i(t - 1) \quad (B.1)
\]

However, it has been observed that some inbound and/or outbound flights are missing from the ASQP dataset. As a result, \(g_i(t)\) has been observed to slowly drift 

\(^1\)However most aircraft still need to be parked a gate for some time to load or unload passengers and cargo.
up or down, by as much as 50 aircraft over a year. To minimize the effects of these missing flights, a more robust gate accounting procedure was developed. In this procedure, each day $D$ is considered individually, and the number of aircraft parked at the gates is now counted relatively to what it was at the beginning of the day\textsuperscript{2}.

Define:

\[
g_i^0(D) = g_i(\text{beginning of day } D)
\]

\[
= \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of day } D.
\]

Note that $g_i^0(D)$ cannot be precisely measured in the ASQP dataset because, as mentioned earlier, some flights are not recorded.

Then define for all time periods $t$ within day $D$:

\[
\delta_i(t) = g_i(t) - g_i^0(D)
\]

In other words, $\delta_i(t)$ is the difference between the number of aircraft of airline $i$ currently at the gates and the number of aircraft that were at the gates when the day started.

Define for each day $D$:

\[
\gamma_i(D) = \max_{t \in D} \delta_i(t)
\]

\[
\lambda_i(D) = \min_{t \in D} \delta_i(t)
\]

\[
\Delta_i(D) = \gamma_i(D) - \lambda_i(D)
\]

Note that $\lambda_i(D)$ is usually negative because many aircraft are kept at the gates overnight and leave in the morning before arriving aircraft reach the airport.

Figure B-1 illustrates the previous definitions.

Histograms of $\gamma_i(D)$ and $\lambda_i(D)$ were compiled for each major airline at Boston Logan in 1996. Typical histograms are shown in Figure B-2.

\textsuperscript{2}The "beginning of the day" is chosen to be 4 am, because delayed operations from the previous day often extend past midnight.
Figure B-1: Definition of gate utilization variables.

Figure B-2: Histograms of $\gamma_i$ and $\lambda_i$ for a major airline at Boston Logan in 1996.
Note: if at some time during day $D$, airline $i$ had no aircraft parked at its gates, then we would have:

$$
\lambda_i(D) = -g_i^0(D)
$$

Likewise, if at some time during day $D$, airline $i$ had all of its gates (and ramp and hangar spaces) occupied, then we would have:

$$
\gamma_i(D) = G_i - g_i^0(D)
$$

And if both of these events happened on a given day $D$, then we would have:

$$
\Delta_i(D) = G_i
$$

which means that the gate capacity of the airline could be measured from the ASQP dataset.

However, in general

$$
\lambda_i(D) \geq -g_i^0(D)
$$

$$
\gamma_i(D) \leq G_i - g_i^0(D)
$$

so that:

$$
\Delta_i(D) \leq G_i.
$$

Thus $\max_{D \in \text{year}} \Delta_i(D)$ is a lower bound on the gate capacity of airline $i$. A typical histogram of $\Delta_i(D)$ is given in Figure B-3. Table B.1 shows $\max_{D \in 1996} \Delta_i(D)$ for the nine major airlines included in the ASQP database, along with the values reported in a gate study prepared by the Massachusetts Port Authority (MPA) in 1996.

For most airlines the value of $\max_{D \in 1996} \Delta_i(D)$ is much higher than the capacity given by the MPA report. This could reflect two factors:

- use of ramp or hangar spaces to store aircraft (these spaces are not included in the MPA report);
- incomplete or obsolete reporting of gate allocation in the MPA report.
Figure B-3: Histograms of $\Delta_i$ for a major airline at Boston Logan in 1996.

<table>
<thead>
<tr>
<th>Airline #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASQP lower bound</td>
<td>19</td>
<td>11</td>
<td>15</td>
<td>5</td>
<td>4</td>
<td>9</td>
<td>6</td>
<td>16</td>
<td>25</td>
</tr>
<tr>
<td>MPA capacity</td>
<td>10</td>
<td>6</td>
<td>11</td>
<td>4</td>
<td>1</td>
<td>6</td>
<td>4</td>
<td>6</td>
<td>20</td>
</tr>
</tbody>
</table>

Table B.1: Comparison of gate capacity for each airline: ASQP-derived lower bound ($\max_{D \in 1996} \Delta_i(D)$) and MPA reported capacity.
B.3 Effect of departure control scheme on gate shortage

The gate utilization variables in the control law simulation are defined in the same manner as the historical (or "actual") variables defined in the previous section:

\[ \tilde{g}_i(t) = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of time period } t \text{ in a simulation run.} \]

\[ \tilde{g}_i^0(D) = \tilde{g}_i(\text{beginning of day } D) = \text{number of jet aircraft of airline } i \text{ parked at the gates (or on a ramp or in a hangar) at the beginning of day } D \text{ in a simulation run.} \]

\[ \tilde{\delta}_i(t) = \tilde{g}_i(t) - \tilde{g}_i^0(D) \]

Recall that the simulation uses the reported historical pushbacks and arrivals found in the ASQP database, and that the only effect of the control law implemented in the simulation is to delay some pushbacks by a small amount of time. Hence the simulation starts each day \( D \) with the actual number of aircraft that was found to be parked at the gates:

\[ \tilde{g}_i^0(D) = g_i^0(D) \]

However in general \( \tilde{\delta}_i(t) \geq \delta_i(t) \), because the control law holds some aircraft at their gates for some time before allowing them to push back.

A gate shortage is defined as any time period \( t \) of any day \( D \) such that:

\[ \tilde{\delta}_i(t) \geq \gamma_i(D) \]

This definition is somewhat conservative\(^3\).

Figure B-4 illustrates the previous definitions.

\(^3\)Recall that unless the airline had all of its gates simultaneously occupied at some time during day \( D \), \( \gamma_i(D) \) underestimates how many aircraft the airline could accommodate.
Figure B-4: Definition of gate utilization variables in the simulation.
Gate shortages were recorded in the simulation in each runway configuration with different control law parameters. Define:

\[ \tilde{\epsilon}_{i,j}(N_c) = \text{under the control law with parameter } N_c, \text{ number of time periods in a year when airline } i \text{ would have needed exactly } j \text{ more gates to avoid a gate shortage} \]

\[ = \text{under the control law with parameter } N_c, \text{ number of time periods in a year when } \tilde{\delta}_i(t) = \gamma_i(D) + j. \]

Table B.2 gives the values of \( \tilde{\epsilon}_{i,j}(N_c) \) in runway configuration 9 for all airlines. Since configuration 9 was in use for about 23,900 minutes in 1996, a value of \( \tilde{\epsilon}_{i,j}(N_c) \) of 100 minutes means that airline \( i \) was missing \( j \) gates 0.4% of the time.

<table>
<thead>
<tr>
<th>Airline #</th>
<th>( N_c = 4 )</th>
<th>( N_c = 5 )</th>
<th>( N_c = 6 )</th>
<th>( N_c = 7 )</th>
<th>( N_c = 8 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( j = 1 ) 57.0</td>
<td>27.7</td>
<td>12.4</td>
<td>8.1</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 1.1</td>
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<td>0.0</td>
<td>0.2</td>
<td>0.0</td>
</tr>
<tr>
<td>2</td>
<td>( j = 1 ) 116.8</td>
<td>63.7</td>
<td>35.2</td>
<td>23.1</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>3</td>
<td>( j = 1 ) 88.6</td>
<td>43.0</td>
<td>21.3</td>
<td>14.7</td>
<td>7.3</td>
</tr>
<tr>
<td></td>
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<td>1.0</td>
<td>0.8</td>
<td>0.9</td>
<td>0.3</td>
</tr>
<tr>
<td>4</td>
<td>( j = 1 ) 73.5</td>
<td>32.8</td>
<td>15.3</td>
<td>1.0</td>
<td>5.8</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 1.1</td>
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<td>0.0</td>
<td>0.2</td>
<td>0.0</td>
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</tr>
<tr>
<td></td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>6</td>
<td>( j = 1 ) 57.9</td>
<td>25.2</td>
<td>11.6</td>
<td>6.7</td>
<td>2.6</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 0.1</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>7</td>
<td>( j = 1 ) 31.6</td>
<td>11.6</td>
<td>5.3</td>
<td>2.8</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>8</td>
<td>( j = 1 ) 62.6</td>
<td>38.0</td>
<td>19.5</td>
<td>8.9</td>
<td>5.0</td>
</tr>
<tr>
<td></td>
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<td>0.5</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>9</td>
<td>( j = 1 ) 199.0</td>
<td>99.9</td>
<td>48.5</td>
<td>27.2</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 3.3</td>
<td>0.7</td>
<td>0.2</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>Average</td>
<td>( j = 1 ) 76.4</td>
<td>38.0</td>
<td>18.8</td>
<td>10.3</td>
<td>6.2</td>
</tr>
<tr>
<td></td>
<td>( j = 2 ) 0.8</td>
<td>0.3</td>
<td>0.1</td>
<td>0.2</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Table B.2: Effect of control law on gate shortage at Boston Logan: values of \( \tilde{\epsilon}_{i,j}(N_c) \) (in minutes) for various values of \( N_c \) in configuration 9 in 1996 (averaged over 10 simulation runs).

**Notes on Table B.2:**

1. All values of \( \tilde{\epsilon}_{i,j}(N_c) \) were 0 for \( j \geq 3 \) regardless of \( N_c \).
2. The average value of $\tilde{e}_{i,1}(N_c)$ over all airlines for $N_c = 6$ is 18.8 minutes, which was rounded to 19 minutes in the last column of table 4.8 ("Impact of the control law on on-time performance and gate shortage").

Recall that for $N_c = N_{sat} = 6$ in this configuration, the control law would reduce runway queueing time by 24.6%\(^4\). Table B.2 indicates that for this choice of $N_c$ it would be quite uncommon for most airlines to run out of aircraft parking space: the time when they would be one gate short varies between 0 and 48.5 minutes, out of 23,900 minutes of operations, and they would almost never be more than one gate short.

These results could seem quite optimistic to those who are familiar with Boston Logan airport operations. Recall that they rest on two important assumptions:

- aircraft parking space is defined here to include gates, ramp and hangar space routinely used by the airlines.

- the amount of aircraft parking space that is deemed available to each airline on a given day is the maximum that they have been observed to use that day.

However this maximum might reflect undesirable and / or unsustainable operations (e.g. it could reflect many aircraft being towed to and from the hangars).

A more detailed on-site study of gate utilization would be required to decide whether these assumptions are reasonable, and whether the gate shortage results presented in this appendix are accurate.

\(^4\)As seen in Paragraph 4.4.2.
Bibliography


   Computer program available at
   http://www.epa.gov/oms/regs/nonroad/aviation/faeed21.zip

   User’s manual available at


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