Evaluating Airline Delays: The Role of Airline Networks, Schedules, and Passenger Demands

by

Ying Zhu

Bachelor of Arts in Mathematics (2006)
Carroll College, Helena, MT, USA

Submitted to the Department of Civil and Environmental Engineering
In Partial Fulfillment of the Requirements for the Degree of

Master of Science in Civil and Environmental Engineering

at the

Massachusetts Institute of Technology

February 2009

Signature of Author ....
Department of Civil and Environmental Engineering
November 18, 2008

Certified by...   ....
Cynthia Barnhart
Professor of Civil and Environmental Engineering
Thesis Supervisor

Accepted by ....
Daniele Veneziano
Chairman, Departmental Committee for Graduate Students

Evaluating Airline Delays: The Role of Airline Networks, Schedules, and Passenger Demands

By

Ying Zhu

Submitted to the Department of Civil and Environmental Engineering
on November 18, 2008 in Partial Fulfillment of the
Requirements for the Degree of Master of Science in Civil and Environmental Engineering

ABSTRACT

In this thesis, we develop a framework for analyzing airlines' operational performances under different strategic decisions. A detailed study is conducted to compare differences between a major U.S. legacy carrier and a major U.S. low-cost carrier in terms of their scheduling practices, flight-based delays and on-time performances, network operations and mix of passengers, as well as passenger delays and disruptions. One major contribution of this thesis is that the framework we develop to evaluate airlines' performances is not restricted by the availability of proprietary airline data and can be adopted to estimate itinerary-based passenger demand for any U.S. airline included in the Bureau of Transportation Statistics database. Moreover, in this thesis, we compute delay for local and connecting passengers and provide a powerful tool for scenario analysis. Further, we: (1) identify root causes of delays as well as the impact throughout the network; (2) gain insights about how passenger delay can be reduced with different scheduling practices; and (3) guide the design of on-time performance metrics.

Differences in scheduling practices, network operations, passenger mix, aircraft delays, and passenger delays between different airlines arise from carrier-specific characteristics. These characteristics should be considered when designing on-time performance metrics. Characteristics specific to the legacy carrier are: (1) its hubs experience heavy traffic volume and are often subject to ground delay programs (GDPs) caused by poor weather conditions; and (2) it operates banked hubs where a set of arriving flight legs are scheduled closely with a set of departing flight legs to allow passenger connections between arriving and departing flight legs. Characteristics specific to the low-cost carrier are: (1) it tends to fly into locations that are less impacted by weather conditions and less frequently subjected to GDPs; (2) passenger traffic is

distributed more evenly in the system, unlike the case of the legacy carrier in which a much larger portion of passengers connect through the major hubs; and (3) it has de-peaked schedules at the major airports which allow the carrier to achieve higher efficiency in turning aircraft. Another important distinction between the two airlines that needs to be considered when designing on-time performance metrics is: the ratio of passenger delay (especially disrupted passenger delay) to operated flight delay for the low-cost carrier was higher than the corresponding value for the legacy carrier. This difference indicates that flight-specific on-time performance metrics that ignore airline heterogeneity can be an inaccurate measure of passenger experiences.

In this thesis, scenario representations pertaining to various levels of airport traffic under different weather conditions are analyzed within our framework. We measure passenger delays (that is, the positive difference between the actual arrival time of the passenger at his/her destination and the scheduled arrival time) and passenger disruptions, with a passenger disruption defined as a passenger who is re-booked on an itinerary other than that planned due to a missed connection or flight cancellation. Our results show that for the legacy carrier, an increase in flight operations of one percent on the "high-delay" day translates to an increase in the percentage of disrupted passengers (average disrupted passenger delay) of 22.2% (3.1%); for the low-cost carrier, an increase in flight operations of one percent only increases the percentage of disrupted passengers (average disrupted passenger delay) by 12.3% (2.7%). The above statistics suggest that under poor weather conditions, increasing flight operations at busy airports, compared to non-congested airports, can cause a much greater increase in passenger delay and disruptions when airport capacity is reduced by adverse weather condition.

Thesis Supervisor: Cynthia Barnhart
Title: Professor of Civil and Environmental Engineering

ACKNOWLEDGEMENTS

I wish to take this opportunity to thank all the people responsible for my successful graduation from the department of Civil Engineering at MIT. It was an honor to have obtained graduate education from a premier institution like MIT, and I consider myself extremely fortunate for the same.

First, I would like to thank my advisor, Professor Cynthia Barnhart. Her insightful ideas and expertise in the field contributed to this thesis in large measures. She has been a very understanding mentor and trustful friend.

Deep appreciation goes to Professor Moshe Ben-Akiva and Professor Amedeo Odoni for their guidance, support, and suggestions. Also, I would like to thank George Kocur, Professor Nigel Wilson, and Professor Jorge Vera.

My friends at MIT (Sean, Marty, Hazem, David, Maya, Mallory, Virot, Vikrant, Varun, Andre, Lavanya, Claire, Miao, and the rest - too many names to mention) made this place a home away from home. I never ever felt out of my comfort zone at any point of my stay at MIT, and the credit goes to a highly jovial and friendly batch that I was lucky to be a part of. In particular, Gareth, Sarvee, and Samiul were great foils during my tough times, and I am very grateful for that.

I also thank the supportive staff of the Civil Department, in particular, Tina, Patty, and Maria, for clearing away all the administrative issues with an ever-present smile and a set of ever-ready jokes.

Above all, I thank my family: my parents, who define me and whatever I have achieved so far in my life.

Contents

1 Introduction 15
1.1 Operations Service Reliability and Customer Satisfaction 15
1.2 Flight Delay and On-Time Performance Measurement in the U.S. 17
1.3 Causes of Flight Delays 20
1.4 Airline Scheduling Practice 21
1.5 Passenger Delays 22
1.6 Data for the Assessment of Airline Operational Performance 23
1.7 Thesis Contributions 25
1.8 Thesis Outline 26

2 Schedule Padding Analysis 29
2.1 Introduction 29
2.2 Methodology 30
2.3 Slack Time Statistics 31
2.3.1 Airport-Specific PTT and ATT Comparisons 32
2.3.2 Arc-Specific PBLK and ABLK Comparisons 37
2.3.3 Ground Delay Programs 38
2.3.4 Explanations of Planned Differences among the Airlines in Scheduling Slack Time 39
2.3.5 Peaking vs. De-peaking 40

3 Flight Delay and Cancellations 42
3.1 Introduction 42
3.2 Information of Flight Performance from the BTS Data 42
3.2.1 Flight Performance Statistics 42

3.2.2 Causes of Flight Cancellations and Delays 44
3.2.3 Weighted 15-OTP Arrival Rates 47
3.3 Independent Delay and Propagated Delay 51
3.3.1 Computation of the Independent and Propagated Delay 52
3.3.2 PD, IDD, and IAD Results 55
3.3.3 IDD, IAD, and PD Results by Airport....56

4 Passenger Demand and Delay Estimation 65
4.1 Literature Review 65
4.2 Contributions of Our Methodology....66
4.3 Data Descriptions 68
4.4 The 3-Stage Approach....68
4.4.1 Itinerary Generation Algorithm (IGA)....69
4.4.2 Passenger Allocation Process (PAP)....71
4.4.3 Passenger Delay Calculator (PDC) 79

5 Passenger Delay Analysis 86
5.1 Introduction....86
5.2 Network Structure and Passenger Mix 86
5.3 Load Factors 94
5.4 Passenger Delay Statistics 96
5.5 Passenger Disruption Analysis 114
5.6 Disruption Analysis by Airport 117
5.6.1 Aggregating Disruptions by Airport 117
5.6.2 Percentage of Disruptions by Airport 121

6 Conclusions....128
6.1 Summary Findings....128

6.2 Future Directions 137
Bibliography 141

List of Figures

1-1 Distribution of passenger complaints in July, 2006 16

1-2 Overall causes of flight delay for July, 2007 21

2-1 July 8: PTT comparison between the common airports of the two airlines 34

2-2 July 12: PTT comparison between the common airports of the two airlines 34

2-3 July 8: ATT comparison between the common airports of the two airlines 35

2-4 July 12: ATT comparison between the common airports of the two airlines 35

2-5 July 8: Comparison of (ATT-PTT) between the airlines' common airports 36

2-6 July 12: Comparison of (ATT-PTT) between the airlines' common airports 36

3-1 Causes of flight delay for Airline A on July 8 (left) and July 12 (right) in 2006 46

3-2 Causes of flight delay for Airline B on July 8 (left) and July 12 (right) in 2006 46

3-3 Scheme for computing PD, IDD, and IAD 52

3-4 Airline A (07/08/2006): IDD, IAD, and PD by airport 59

3-5 Airline A (07/12/2006): IDD, IAD, and PD by airport 59

3-6 Airline B (07/08/2006): IDD, IAD, and PD by airport 60

3-7 Airline B (07/12/2006): IDD, IAD, and PD by airport 60

4-1 The framework of the Itinerary Generation Algorithm (IGA), Passenger Allocation Process (PAP), and Passenger Delay Calculator (PDC) 67

4-2 Passenger Delay Calculator schematic 83

4-3 Passenger disruption checking algorithm 84

5-1 Market share in Airline A's (left) and Airline B's (right) total enplaned passengers 88

5-2 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 1 89

5-3 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 2 89

5-4 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 3 90

5-5 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 1 90

5-6 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 2 91

5-7 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 3 91

5-8 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 1 92

5-9 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 2 92

5-10 Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 3 93

5-11 Percent of Flight Legs with Load Factor Greater than or Equal to Various Levels in July 2006 96

5-12 Cumulative distributions of passenger delays (among all delayed passengers) .. 112

5-13 Cumulative distributions of passenger delays (among all passengers) 112

5-14 Cumulative distributions of disrupted passenger delays (among disrupted passengers) 113

5-15 Cumulative distributions of disrupted passenger delays (among all passengers) 113

5-16 Number of disrupted passengers in each two-hour time window 116

5-17 Percent of disrupted passengers at different airports on July 8 118

5-18 Percent of disrupted passengers at different airports on July 12 118

5-19 Percent of disrupted passengers due to cancelled flights at different airport of

Airline B on July 8 119
5-20 Percent of disrupted passengers due to missed connections at different airport of Airline B on July 8 119
5-21 Percent of disrupted passengers due to cancelled flights at different airports on July 12 120
5-22 Percent of disrupted passengers due to missed connections at different airport on July 12 120
5-23 The percentage of disrupted passengers contributed by different airport 124
5-24 The percentage of disrupted passengers contributed by certain airports 124
5-25 The percentage of disrupted passengers due to cancelled flights contributed by different airports 125
5-26 The percentage of disrupted passengers due to cancelled flights contributed by different airports 125
5-27 The percentage of disrupted passengers due to missed connections contributed by different airports 126
5-28 The percentage of disrupted passengers due to missed connections contributed by different airports 126
6-1 Scheme of the sensitivity analysis 139

List of Tables

1-1 Percentage of flight operations arriving on time by carrier in May 2008....................18

1-2 Ranking of major airport on-time arrival performance in May 2008..........................19

2-1 Formulas for computing PTT, ATT, ATTS, PBLK, ABLK, ABLKS, and ATS 30

2-2 The average PTT, ATT, ATTS, PBLK, ABLK, ABLKS, and ATS per flight 31

2-3 Arrival delay, PBLK, and ABLK for common arcs on July 8, 2006 38

2-4 Arrival delay, PBLK, and ABLK for common arcs on July 12, 2006 38

3-1 Flight delay statistics based on ASQP 43

3-2 Ranking of major airport on-time arrival performance in July 2006...........................48

3-3 Weighted major airport on-time arrival performance in July 2006 of Airline A........49

3-4 Weighted major airport on-time arrival performance in July 2006 of Airline B 50

3-5 Formulas for computing Slack, PD, IDD, and IAD 53

3-6 The average PD, IDD, and IAD (in minutes)..55

3-7 Average IDD, IAD, and PD per flight (in minutes)..63

3-8 Changes in IDD, IAD, and PD per flight between July 8 and July 12 64

5-1 Daily utilization per aircraft for Airline A and Airline B 94

5-2 Passenger and flight delay statistics 97

5-3 Absolute differences in passenger and flight delay statistics 98

5-4 Ratios in passenger and flight delay statistics...99

5-5 The average waiting time per passenger until the next available itinerary 106

5-6 The ratios per passenger of the number of recovery alternatives, scheduled waiting time, and actual waiting time of Airline A to those of Airline B, respectively 106

5-7 Degree of passenger disruptions 107

5-8 Changes (%) in passenger and flight delay statistics from July 8 to July 12, 2006...110

5-9 Disrupted passengers due to flight cancellations and missed connections..........114

6-1 Ratios of passenger delay to flight delay 134

Chapter 1

Introduction

Owing to the growing economy of the 1990's, airlines increased service and sometimes scheduled more flights than busy airports could handle, even in optimal weather conditions. According to the Bureau of Transportation Statistics (BTS), from 1990 to 2006, the number of flights operated by commercial airlines in the United States grew from 6.6 million in 1989 to 8.0 million in 2006, a 21% increase. In that same period, airport capacity is increased by only 1%. As more and more flights were scheduled at congested airports, ground congestion became a major hindrance to efficient operations. One indicator is that aircraft taxi-out times at major US airports increased sharply: the number of flights with taxi-out times exceeding one hour increased by 165% from 1995 to 2000, from 17,331 flights in 1995 to 45,993 flights in 2000 (Mead (2001) [22]). Furthermore, the unbalanced increase in flight operations relative to total airport capacity caused severe system congestion, and numerous flight delays as well as cancellations, adversely affecting the traveling public.

1.1 Operations Service Reliability and Customer Satisfaction

Although flight schedules and ticket prices have proven to be the main drivers of airline profitability (Gopalan and Talluri (1998) [16]), studies show that customer satisfaction and loyalty drive long-term profitability (Heskett et al. (1994) [18]). Because the airline industry is a highly competitive business, high service reliability can be a major advantage to attract and retain passengers. In particular, business passengers who tend to be more time sensitive (Belobaba and Simpson (1982) [2]) are especially valuable to airline profitability. Similarly, low service reliability can result in decreasing average fares (Janusewski (2002) [19]).

To provide consumers information on the quality of services provided by the airlines, the current Department of Transportation (DOT) Air Travel Consumer Report uses six types of information to evaluate airline service reliability: (1) flight delays, (2) mishandled baggage, (3) oversales, (4) consumer complaints, (5) incidents involving the loss or injury of animals during air transportation, and (6) customer service reports. (1), (2), and (3) are reported by the BTS; (4) and (5) are reported by the DOT Aviation Consumer Protection Division based on complaints submitted by customers; and (6) is generated from information submitted to the Transportation Security Administration related to airline and airport security. As illustrated in Figure 1-1 (Air Travel Consumer Report (2006) [13]), the most common complaints are related to flight problems, defined as "flight cancellations, delays, or any other deviations from schedule, whether planned or unplanned" by the DOT.

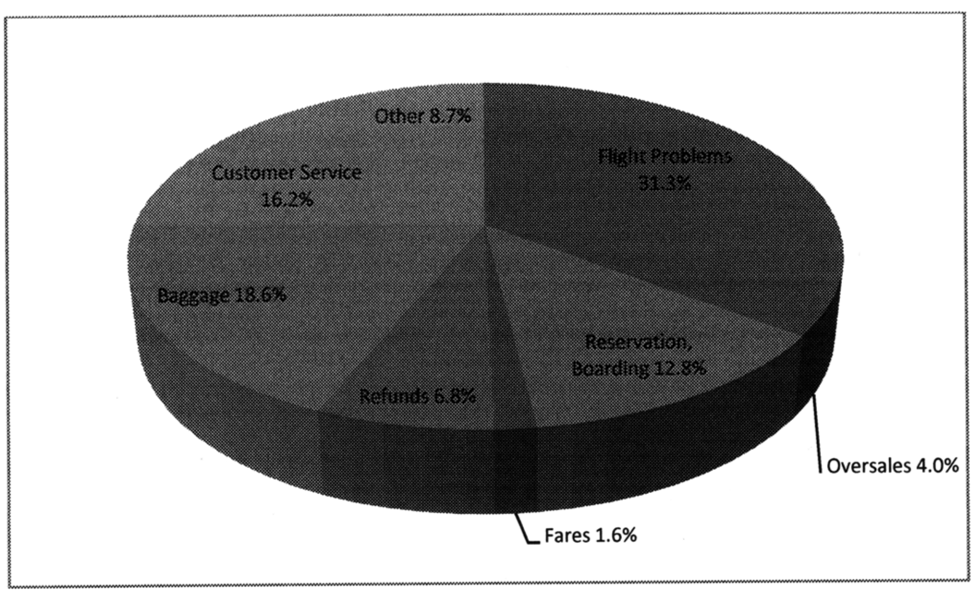


Figure 1-1: Distribution of passenger complaints in July, 2006

1.2 Flight Delay and On-Time Performance Measurement in the U.S.

Since 1987, flight delay statistics have been published in the Air Travel Consumer Report on a monthly basis and maintained in the Airline Service Quality Performance (ASQP) database, which is publicly accessible. The major airlines in the U.S. (defined as airlines generating revenues of $1 billion or more annually) are mandated by federal law to provide flight operation information, including actual departure time, arrival time, cancellation and diversion, for each domestic U.S. flight serviced by jet aircraft. In 2006, 18 U.S. carriers met this requirement.

The metric currently employed by the DOT and airlines to estimate on-time performance is the *15 minutes on-time performance (15-OTP)*, also referred to as the *airline dependability statistic.* According to this metric, a flight is considered to be on time if it arrives within 15 minutes or earlier of its scheduled arrival time and a canceled flight is classified as a delayed flight. Based on the Air Travel Consumer Report for May 2008 [13], the industry achieved an average 79.0% on-time arrival rate for all airports reported. Hawaiian Airlines reported the best performance with 88.9% on-time arrivals, while American Airlines reported the worst performance with 67.3% on-time arrivals. In terms of airports, Newark, NJ (EWR) experienced the worst on-time arrival performance of 63.16% and Salt Lake City (SLC) achieved the best performance of 88.66%. Table 1-1 lists the percentage of flight operations arriving on time by carrier. Table 1-2 displays the ranking of major airports' on-time arrival performance. For more details on on-time performance, see http://airconsumer.ost.dot.gov/reports/index.htm.

	AT ALL REPORTABLE AIRPORTS	
CARRIER	NUMBER OF AIRPORTS REPORTED	PERCENT OF ARRIVALS ON TIME
HAWAIIAN AIRLINES	14	88.9
PINNACLE AIRLINES	114	85.9
AIRTRAN AIRWAYS	57	84.7
SKYWEST AIRLINES	143	84.5
DELTA AIR LINES	91	84.1
ATLANTIC SOUTHEAST AIRLINES	124	83.8
US AIRWAYS	82	83.6
SOUTHWEST AIRLINES	64	80.9
ALASKA AIRLINES	45	80.4
JETBLUE AIRWAYS	46	79.2
NORTHWEST AIRLINES	96	78.9
COMAIR	87	78.4
MESA AIRLINE	116	76.9
FRONTIER AIRLINES	45	76.5
AMERICAN EAGLE	114	76.3
EXPRESSJET AIRLINES	126	76.1
CONTINENTAL AIRLINES	63	75.4
UNITED AIRLINES	81	72.4
AMERICAN AIRLINES	77	67.3
TOTAL		79.0

Table 1-1: Percentage of flight operations arriving on time by carrier in May 2008
Source: Air Travel Consumer Report

Rank	May 2008	%
1	Salt Lake City, UT (SLC)	88.66
2	Baltimore, MD (BWI)	86.65
3	Chicago, IL (MDW)	84.95
4	Orlando, FL (MCO)	84.67
5	Cincinnati, OH (CVG)	84.65
6	Atlanta, GA (ATL)	84.32
7	Tampa, FL (TPA)	84.28
8	Detroit, MI (DTW)	83.99
9	Charlotte, NC (CLT)	83.48
10	Washington, DC (DCA)	82.29
11	Fort Lauderdale, FL (FLL)	81.53
12	Minneapolis/St. Paul, MN (MSP)	81.50
13	Washington, DC (IAD)	79.79
14	Boston, MA (BOS)	79.78
15	Houston, TX (IAH)	79.74
16	Phoenix, AZ (PHX)	79.60
17	Oakland, CA (OAK)	78.96
18	Portland, OR (PDX)	78.50
19	St. Louis, MO (STL)	78.01
20	New York, NY (JFK)	77.27
21	Seattle, WA (SEA)	77.20
22	Las Vegas, NV (LAS)	76.01
23	Denver, CO (DEN)	75.92
24	San Diego, CA (SAN)	75.45
25	Philadelphia, PA (PHL)	75.15
26	Los Angeles, CA (LAX)	75.09
27	Miami, FL (MIA)	74.75
28	Chicago, IL (ORD)	74.07
29	San Francisco, CA (SFO)	71.65
30	Dallas/Ft.Worth, TX (DFW)	70.91
31	New York, NY (LGA)	64.11
32	Newark, NJ (EWR)	63.16

(Percent On-Time)

Table 1-2: Ranking of major airport on-time arrival performance in May 2008
Source: BTS, Airline On-Time Data

1.3 Causes of Flight Delays

The DOT divides the causes of flight delays into five categories[1]:

- Air Carrier Delay: The cause of the cancellation or delay was due to circumstances within the airline's control (e.g. maintenance or crew problems, etc.).
- Extreme Weather Delay: Significant meteorological conditions (actual or forecasted) that, in the judgment of the carrier, delays or prevents the operation of a flight.
- National Aviation System Delay: Delays and cancellations attributable to the national aviation system (NAS) refer to a broad set of conditions -- non-extreme weather conditions, airport operations, heavy traffic volume, air traffic control, etc.
- Security Delay: Delays caused by evacuation of terminal or concourse, re-boarding of aircraft because of security breech, inoperative screening equipment and long lines in excess of 29 minutes at screening areas.
- Late Arriving Aircraft Delay: The previous flight with same aircraft arrived late which caused the present flight to depart late.

By definition of the DOT, a "cancelled" flight refers to "a flight that was not operated, but was in the carrier's computer reservation system within seven days of the scheduled departure." A "diverted" flight refers to "a flight which is operated from the scheduled origin point to a point other than the scheduled destination point in the carrier's published schedule." Figure 1-2 (Air Travel Consumer Report (2007) [13]) depicts the distribution of the overall causes of flight delays for July, 2007. We observe that Late Arriving Aircraft Delay (representing delay propagating to downstream flights) contributes the greatest level of delay among all categories. Also note the percentage of flights delayed as a result of late arriving aircraft (9.87%) is about the same as the percentage of flights delayed by the NAS, extreme weather, and security (8.45% + 1.31%

[1] Source: Air Travel Consumer Report [13]

+ 0.10% = 9.86%). This suggests, on average, for each flight delayed by extreme weather, the NAS, and security, another flight is delayed due to the propagation of this delay. In other words, when a total of 17.91% (8.05% + 1.31% + 8.45% + 0.1%) of flights are delayed, 9.87% of flights have their delay propagated to the next flight in the trajectory.

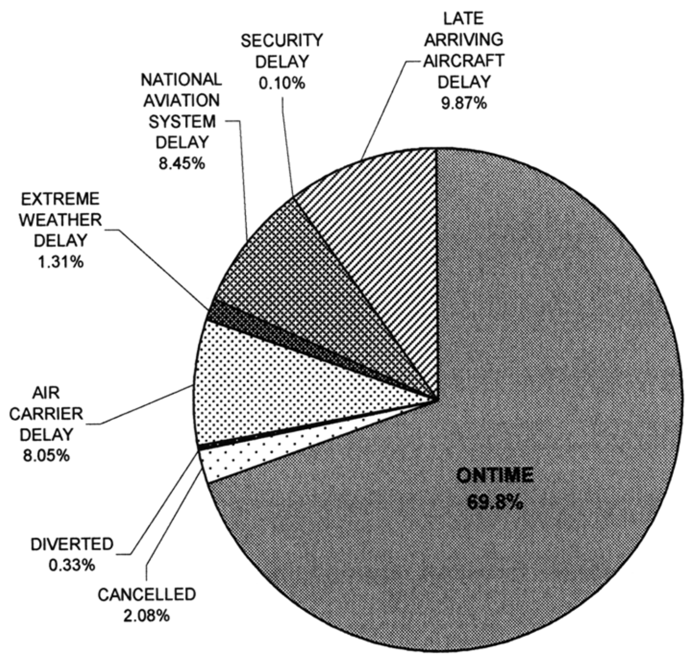


Figure 1-2: Overall causes of flight delay for July, 2007

1.4 Airline Scheduling Practice

Between 1995 and 2000, in an attempt to improve flight on-time performance, U.S. carriers responded to the 15-OTP metric by increasing the scheduled gate-to-gate times, namely block times, for flights (Shumsky (1993) [23] and Hall (1999) [17]). During that period, the total block hours were increased from 10,361,858 to 12,034,337 on average for the major network carriers (Airline Data Project [21]). Caulkins et al. (1993) [11]

argue that airlines operating in congested airports are disadvantaged by the 15-OTP metric compared to airlines flying to less congested secondary airports. This is a result of two factors: (1) ground delay programs are implemented more frequently at these congested airports; and (2) airlines flying into these congested airports are subject to reduced efficiency because they schedule more buffers in their ground turn time in an attempt to respond to this uncertainty. In this thesis, we examine the effects of airport locations and flight scheduling practices on aircraft and passenger delays.

1.5 Passenger Delays

Barnhart and Bratu conducted a study on airline passenger delays and showed that 15-OTP does not accurately measure the amount of passenger delay. They developed an algorithm, called the Passenger Delay Calculator, to compute passenger delay statistics. Using actual passenger bookings and flight operations information from a major US airline, they discovered that simple flight-based statistics tend to underestimate passenger delays because passengers whose travel plans are disrupted by cancelled flights or missed connections (namely, disrupted passengers) experience much longer delays on average than are reported for the corresponding flights. They proposed a new metric based on the number of disrupted passengers and argued that it better represented airline schedule reliability as experienced by passengers than did the existing metric.

In other research, including that of Wang and Sherry (2006) [24] and Ball, Lovell, Mukherjee and Subramanian (2005) [1], similar results have been derived. For instance, Wang (2007) [25] estimates that 40% of the total trip delays accrued by passengers on single segment flights are the result of delays due to cancelled flights, despite that only a very small fraction of fights are cancelled. The remaining 60% of total trip delays are attributed to flight delays. However, unlike the Passenger Delay Calculator developed by Barnhart and Bratu, Sherry and Wang's analysis only considers non-stop segment data and excludes the possibility of disruptions due to missed connections.

1.6 Data for the Assessment of Airline Operational Performance

The major data source for assessing airline operational performance in this thesis comes from BTS. It includes T-100, The Airline Origin and Destination Survey (also known as DB1B), Flight On-Time Performance (also known as ASQP), and the FAA Aircraft Registry Database. The description of each data file is given in the following.

***T-100 Domestic Segment* (*U.S. Carriers*)** contains domestic *non-stop segment* data reported by U.S. air carriers by month. Useful information includes carrier, origin, destination, available capacity, number of scheduled departures, number of performed departures, number of passengers on each flight segment, and load factor when both origin and destination airports are located within the boundaries of the United States and its territories. The number of passengers in this data file is monthly aggregated over each flight segment (BTS (2006) [10]).

DB1B is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the BTS. It consists of 3 parts: DB1B Coupon, DB1B Market, and DB1B Tickets, described as follows.

> ***DB1B Coupon*** provides *coupon-specific* information for each domestic itinerary of the Origin and Destination Survey, such as the operating carrier, origin and destination airports, and number of passengers, fare class, coupon type, trip break indicator, and distance. The number of passengers in this data file is quarterly aggregated over each domestic itinerary and the itineraries do not contain flight schedules (BTS (2006) [6]).

DB1B Market contains *directional market characteristics* of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators (BTS (2006) [7]).

DB1B Ticket contains *summary characteristics* of each domestic itinerary on the Origin and Destination Survey, including the reporting carrier, itinerary fare, number of passengers, originating airport, roundtrip indicator, and miles flown. The number of passengers reported in this data file is quarterly aggregated over each domestic itinerary and the itineraries do not contain flight schedules (BTS (2006) [8]).

Flight On-Time Performance (ASQP) contains daily on-time arrival data for non-stop domestic flights by major air carriers, and provides information such as departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance (BTS (2006) [5]).

FAA Aircraft Registry Database is a database of all aircraft registered in the U.S. We use this database to match an aircraft tail number to an aircraft type. Once the aircraft types are identified, we can obtain the seating capacity information from the target airline's official website (FAA [14]).

In summary, T-100 and DB1B contain only passenger segment or route information (no flight schedule information) and ASQP provides only flight information (no passenger information). The FAA Aircraft Registry Database is used to obtain the flight seating capacity information. Due to the lack of detailed passenger itinerary and booking information, special methods are required in order to quantify passenger delays. In particular, we need algorithms that generate detailed passenger itineraries and estimate passenger demand on each itinerary.

1.7 Definitions

To facilitate the description of our analysis, we introduce the following notations and definitions. A non-stop flight f, also referred to as a flight leg, is associated with a flight number, an origin airport, a destination airport, a *Planned Departure Time, PDT(f),* and a *Planned Arrival Time, PAT(f).* In operations, *AAT(f)* stands for the *Actual Arrival Time* of flight f at the gate and *ADT(f),* the *Actual Departure Time* from the gate. The *Flight Arrival Delay* of flight f, denoted by *FAD(f),* equals *max(AAT(f) - PAT(f); 0)*; the *Flight Departure Delay,* denoted by *FDD(f),* equals *max(ADT(f) - PDT(f); 0).*

A *Scheduled Itinerary, (SI)* is a sequence of scheduled flights serving a group of passengers. The group of passengers on a given *SI* is referred to as a *Scheduled Passenger Type* (*SPT*). If a *SI* corresponding to a given *SPT* has only one flight then, passengers are *local*, otherwise they are *connecting*. For a given day of operations, passengers are served on a sequence of flights, called the *Actual Itinerary* (*AI*). We define an actual passenger type *APT(s,u)* as the group of passengers originally scheduled on *SI s* who actually travel on *SI u*. Other useful definitions are the *Minimum Connecting Time (MCT)*; that is, the minimum time required to walk between the arrival and departure gates of the consecutive flights, and *Maximum Layover Time (MLT)*; that is, the maximum allowable waiting time at a connecting airport between the previous flight's arrival and the next flight's departure. A passenger is *disrupted* if:

- One or more of the flights in his/her scheduled itinerary is canceled; or
- The time between consecutive flights in his/her scheduled itinerary is less than the *MCT*; In this case, the passenger misses connections.

Additionally, in our future discussion, we adopt the conventional definition of *route* (the sequence of one or more flight legs serving an origin/destination airport pair); in other words, flight legs from an origin airport o to a destination airport d constitute a route, while the return flight legs from d to o represent a different route, called the opposite route.

1.8 Thesis Contributions

The primary goal of this thesis is to investigate the differences between a major U.S. legacy carrier (labeled as "Airline A" in this thesis) and a major U.S. low-cost carrier (labeled as "Airline B" in this thesis) in terms of their flight on-time performances, network structures, scheduling practices, and passenger delays. Statistics will be generated for both airlines on two different days in July 2006. The legacy carrier operates a hub-and-spoke network in which three hubs serve 74 airports in the domestic US. The low-cost carrier is the largest airline in the United States by number of passengers carried domestically per year (as of December 31, 2007) and has consistently received the lowest ratio of complaints per passenger boarded of all major US carriers. We select the days such that they represent two scenarios: July 8, 2006 was a "low-delay" day for both airlines as measured by fewer cancellations and higher flight on-time performance; July 12, 2006 was a "high-delay" day with both airlines experiencing more cancellations and greater delays. Additionally, July 8, 2006 was a Saturday while July 12, 2006 was a Wednesday. In general, airlines schedule more flights on weekdays and fewer flights on weekends, which is also the case for both airlines in this study.

We develop a 3-stage approach to quantify passenger delays using only the publicly accessible data described in 1.6. In the first-stage, a new approach is used to generate itineraries; in the second stage, we develop a linear integer programming model to allocate passengers to the itineraries generated in the first stage; and in the third stage, we use the Passenger Delay Calculator to compute passenger delay. The major contribution of our methodology is that it provides a way to generate passenger booking data for all scheduled flights using only publicly accessible data. Unlike previous studies, the 3-stage approach is not restricted by the availability of proprietary airline data and can be adopted to estimate itinerary-based passenger demand for any U.S. airline included in the BTS database. Moreover, it can be used to compute delays for local and connecting passengers and to provide a powerful tool for scenario analysis. Further, it allows us to: (1) identify root causes of delays as well as the impact throughout the network; (2) help gain insights about how passenger delay can be reduced with different scheduling practices; and (3) guide the design of good on-time performance metrics.

1.9 Thesis Outline

The framework we develop in this thesis includes the following objectives:

- Investigate the differences in the placement of slack time, often referred to as schedule "padding," and other scheduling practices among airlines, and provide the rationale behind the differences;
- Examine the sources of aircraft delays for different airlines and identify airports contributing the majority of delays for each airline;
- Quantify and compare passenger delays between the legacy carrier and the low-cost carrier;
- Use quantitative evidence to show that a better OTP metric should take into account the carrier-specific characteristics and reflect passenger delays;
- Discuss future scenarios about trends in the airline industry, such as levels of flight operations; and

- Project passenger delays under different scenario representations within our framework.

We explore the airlines' scheduling practices and the resulting impact on flight on-time performance in Chapter 2. The analysis of flight delays is discussed in Chapter 3. We develop the 3-stage approach to estimate passenger demand and passenger delay in Chapter 4. Comparison of passenger delays between the legacy carrier and the low-cost carrier is made in Chapter 5. Additionally, we establish relationships between passenger delays and flight leg delays, cancellation rates, load factors, network operations, passenger mix, and schedule designs. Chapter 6 provides conclusions and recommendations for future work.

Chapter 2

Scheduling of Slack Time

2.1 Introduction

When designing schedules, airlines usually "pad" their schedules by inserting buffer or slack time. The way airlines pad their schedules can have a significant impact upon on-time performance and passenger delays. There are two methods of schedule "padding." One is to plan slack into the ground turn time (i.e., the ground time to prepare an aircraft for its next departure); the other is to plan slack into the block times (i.e., the gate to gate times including taxi out, flying, and taxi in). Ground slack can reduce departure delays caused by late incoming flights (i.e., propagated delays). However, it has no effect on departure delays attributed to weather conditions, airport operations, heavy traffic volume, air traffic control, etc., which are often referred to as NAS delays. These departure delays in turn cause arrival delays, and hence, ground slack does not help to reduce arrival delays. Slack in block times, however, can reduce the effects of NAS delays and increase on-time arrival performance. This is the case when a planned block time exceeds the actual block time resulting in an actual arrival time at the destination airport that is earlier than expected when adding the planned block time to the actual departure time. In Section 2.2, we derive mathematical formulas, given a flight schedule as planned and as operated, for obtaining planned turn time, actual turn time, actual turn time slack, planned block time, actual block time, and actual block time slack. In Sections 2.3 and 2.4, we apply the methodology from Section 2.2 to obtain relevant statistics for the legacy network carrier and the low-cost carrier. In Section 2.5, we explain the rationale behind the statistics for each airline.

2.2 Methodology

Notations:

- PDT: Planned Departure Time
- ADT: Actual Departure Time
- PAT: Planned Arrival Time
- AAT: Actual Arrival Time
- PTT_{ij}: Planned Turn Time between flight i and flight j
- ATT_{ij}: Actual Turn Time between flight i and flight j
- $ATTS_{ij}$: Actual Turn Time Slack (i.e., the difference between PTT_{ij} and ATT_{ij})
- PBLK: Planned Block Time
- ABLK: Actual Block Time
- $ABLKS_{ij}$: Actual Block Time Slack (i.e., the difference between $PBLK_{ij}$ and $ABLK_{ij}$)
- ATS_{ij}: Actual Total Slack (i.e., the sum of $ATTS_{ij}$ and $ABLKS_{ij}$)

$$PTT_{ij} = PDT_j - PAT_i$$

$$ATT_{ij} = ADT_j - AAT_i$$

$$ATTS_{ij} = PTT_{ij} - ATT_{ij} = (PDT_j - PAT_i) - (ADT_j - AAT_i)$$

$$PBLK_i = PAT_i - PDT_i$$

$$ABLK_i = AAT_i - ADT_i$$

$$ABLKS_{ij} = PBLK_i - ABLK_i = (PAT_i - PDT_i) - (AAT_i - ADT_i)$$

$$ATS_{ij} = ATTS_{ij} + ABLKS_{ij}$$

Table 2-1: Formulas for computing PTT, ATT, ATTS, PBLK, ABLK, ABLKS, and ATS

PDT, ADT, PAT, and AAT are available in the ASQP data[2]. In the following sections, we will present, for each airline, the average statistics, the airport-specific statistics, and arc-specific (airport origin-destination pair for a single flight segment) statistics. Comparisons will be made between the common airports and arcs shared by the legacy network carrier and the low cost-carrier.

2.3 Slack Time Statistics

Table 2-2 lists the average PTT, ATT, ATTS, PBLK, ABLK, ABLKS, and ATS of the legacy network carrier and the low-cost carrier, respectively, on July 8, 2006 and July 12, 2006. The average statistics come from dividing the summary statistics by the number of performed departures for each airline. Therefore, it represents an overall measure of each airline's performance.

Average	PTT	ATT	PTT-ATT = ATTS	PBLK	ABLK	PBLK-ABLK = ABLKS	ATS+ABLKS=ATS
A0708	199.48	215.10	-15.62	522.33	508.80	13.53	-2.09
A0712	171.10	212.80	-41.70	644.35	661.20	-16.85	-58.55
B0708	129.85	169.69	-39.83	558.54	522.05	36.50	-3.33
B0712	148.14	193.69	-45.55	692.07	669.92	22.15	-23.4

Table 2-2: The average PTT, ATT, ATTS, PBLK, ABLK, ABLKS, and ATS per flight (in minutes)

In Table 2-2, a more positive ATTS (ABLKS) means a greater actual turn time slack (actual block time slack) for the airline. A negative ATTS (ABLKS) means the planned buffer was insufficient and as a result, ATT (ABLK) was greater than PTT (PBLK). Notice the following:

[2] That is, the Airline On-Time Performance Data. Available: *http://www.transtats.bts.gov/Tables.asp?DB_ID=120&DB_Name=Airline%20On-Time%20Performance%20Data&DB_Short_Name=On-Time* [5].

- Overall, the daily average PTT and ATT per aircraft were higher for Airline A than for Airline B per day. On the other hand, the average PBLK and ABLK per aircraft were slightly higher for Airline B than for Airline A per day.
- The daily average ATTS was negative for both airlines. However, Airline A had a greater ATTS (than Airline B) on average per aircraft while Airline B had a greater ABLKS (than Airline A) on average per aircraft per day. This difference implies Airline A has more slack than Airline B in its ground turn time, while Airline B has more slack than Airline A in its block time.
- The average RTB was also negative for both airlines. On July 8, the ATS was just below zero for both airlines but on July 12, Airline A had an ATS value that was more than two times than that of Airline B. This suggests that Airline A is much more severely impacted, as measured by delay minutes, than Airline B when NAS delays are present.

2.3.1 Airport-Specific PTT and ATT Comparisons

We compute the PTT and ATT between common airports of Airline A and Airline B. We index these airports from 1 to 39. Figure 2-1 to Figure 2-4 give comparisons in PTT and ATT of common airports shared by both Airline A and Airline B. Again, we see Airline A tends to plan much higher ground turn times. Almost every airport of Airline A has a greater PTT than that of Airline B. Furthermore, notice Airline B plans almost identical amounts of PTT at each airport. Figure 2-5 and Figure 2-6 depict the differences between ATT and PTT of each airline on July 8, 2006 and July 12, 2006, respectively. For illustration purposes, we are subtracting PTT from ATT in Figure 2-5 and Figure 2-6. Hence, a positive value indicates a negative ATTS or insufficient planned buffer. We observe:

- On July 8, 2006, both airlines' ATT values were only slightly greater than their PTT values (Figure 2-5). Further, the differences were increased on July 12, 2006 for both airlines (Figure 2-6). Overall, the differences of ATT and PTT for Airline B took on positive but insignificant values while Airline A had some negative values but several of its airports showed very significant positive differences.
- Airline B's performance (i.e., the difference of ATT and PTT) at different airports was more homogenous and less affected during the "high-delay" day than Airline A. Airline B's value of actual minus planned turn time was less than twenty minutes except for one 40-minute instance, while Airline A's value was highly variable, with several instances at or exceeding 60 minutes and one as great as more than 150 minutes.

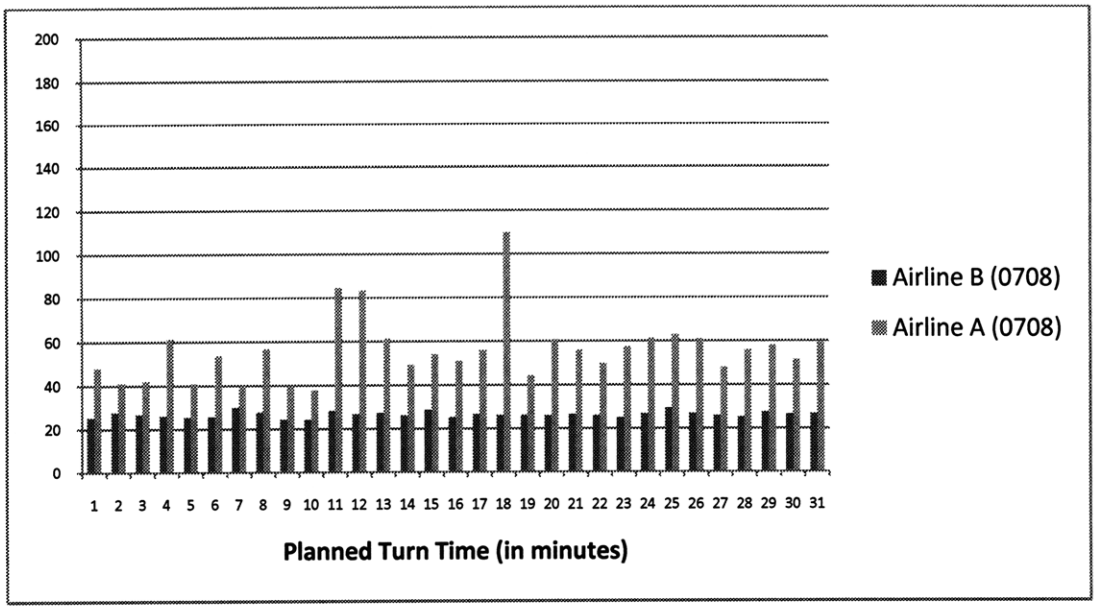


Figure 2-1: July 8: PTT comparison between the common airports of the two airlines

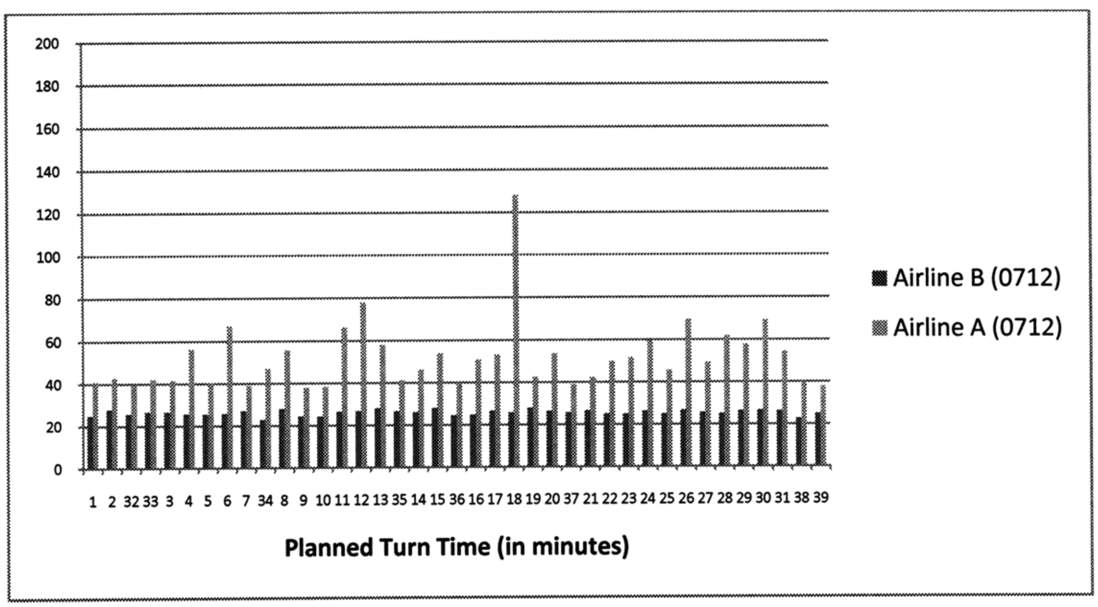


Figure 2-2: July 12: PTT comparison between the common airports of the two airlines

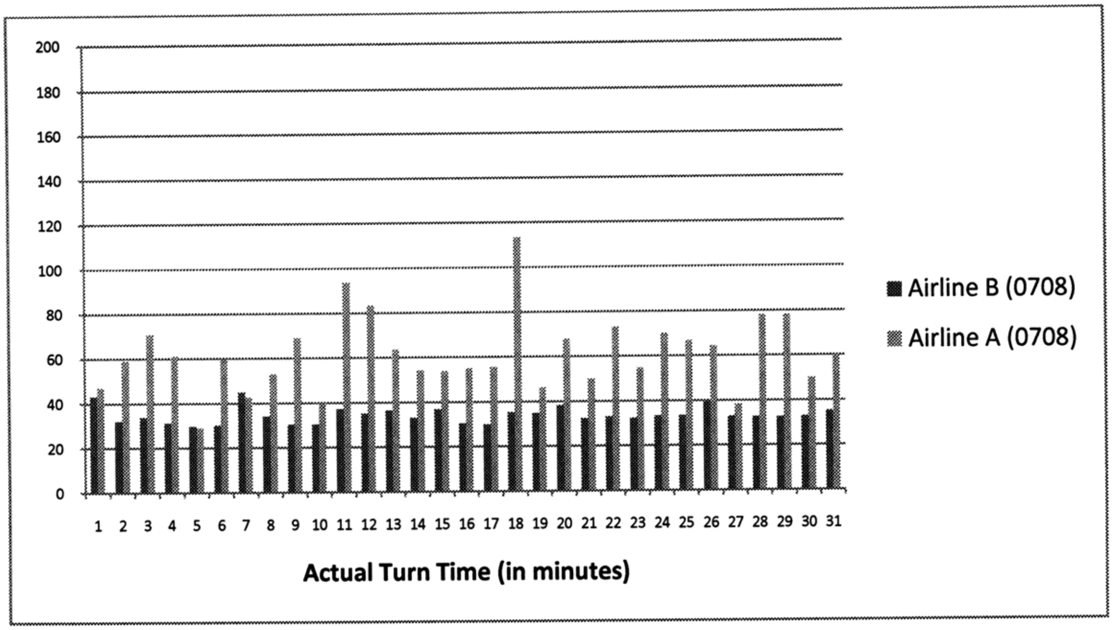


Figure 2-3: July 8: ATT comparison between the common airports of the two airlines

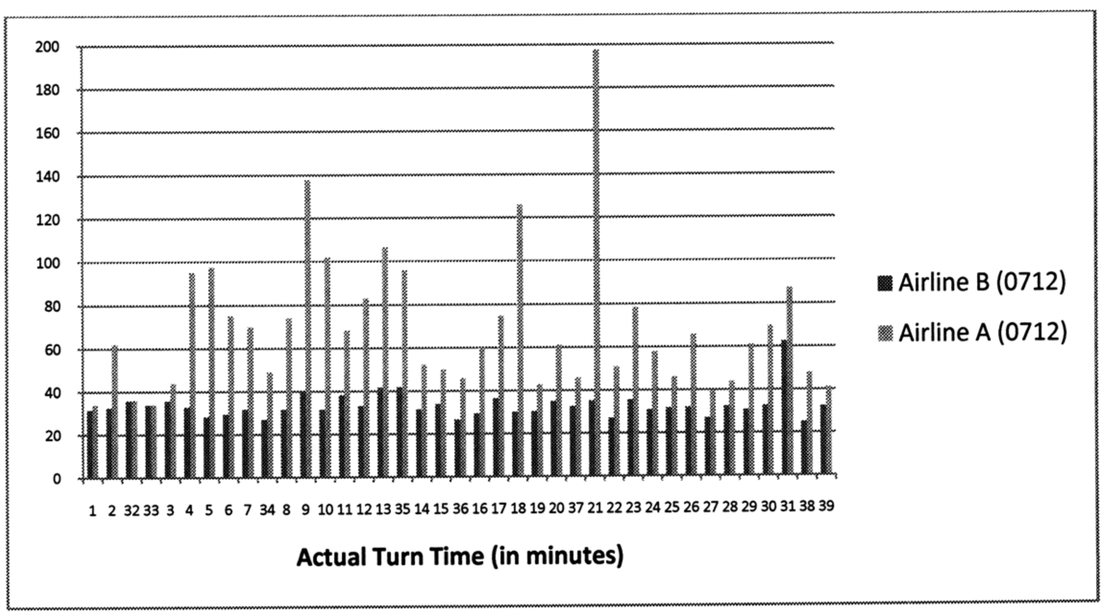


Figure 2-4: July 12: ATT comparison between the common airports of the two airlines

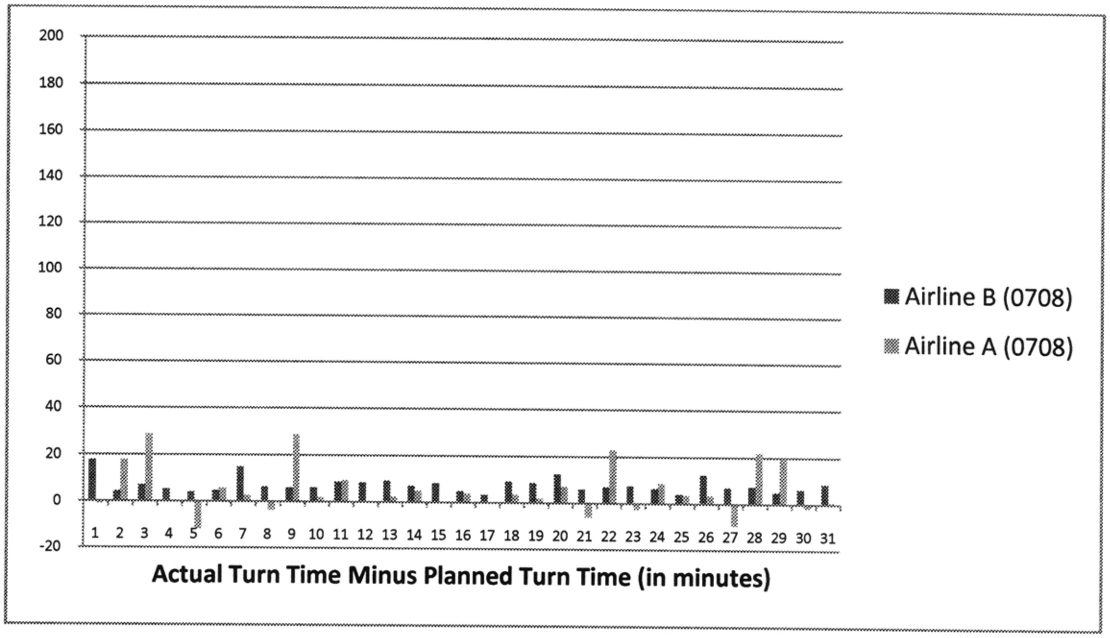


Figure 2-5: July 8: Comparison of (ATT-PTT) between the airlines' common airports

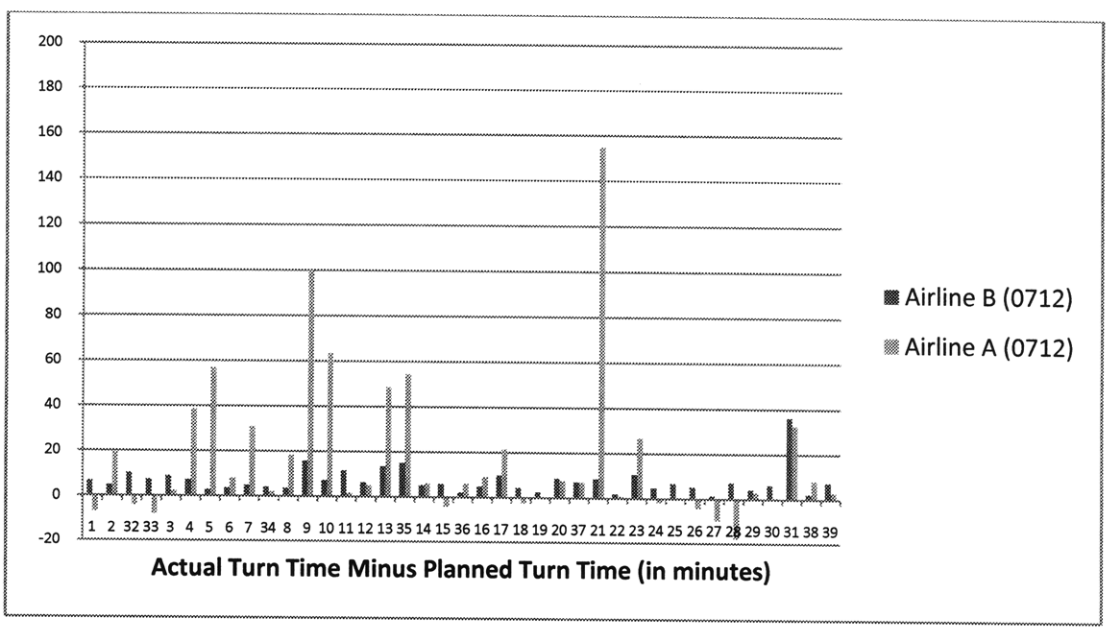


Figure 2-6: July 12: Comparison of (ATT-PTT) between the airlines' common airports

2.3.2 Arc-Specific PBLK and ABLK Comparisons

Previous analysis focuses on the comparisons between the common airports of Airline A and Airline B in PTT, ATT, and ATTS. In this section, the common arcs of the two airlines are examined. Table 2-3 and Table 2-4 list the average arrival delays, PBLK, ABLK, and ABLKS of each airline on July 8, 2006 and July 12, 2006, respectively. We observe the following:

- Airline A and Airline B do not share many common arcs in their network operations. This implies Airline A and Airline B have very different network structures.
- For most of the common arcs, we see Airline B requires less actual block time than Airline A and although the planned block times of A and B are not so different, the effect is that Airline B has more slack in its block times as indicated by its more positive ABLKS values, and in doing so absorbs arrival delays to reduce the downstream propagation of delays. This result is consistent with our previous findings on the average ABLKS comparisons between Airline A and Airline B.
- Airline B must be delayed in departing Airport 20 because the arrival delay exceeds the difference in actual minus planned block times. This is not true for Airline A, so it suggests the delays are related to Airline B's operation not to NAS conditions in Airport 20.

Origin Airport Index	Dest Airport Index	Avg. Arrival Delay (Airline B) minutes	Avg. Arrival Delay (Airline A) minutes	PBLK (Airline B) hours\minutes	ABLK (Airline B) hours\minutes	ABLKS (Airline B) hours\minutes	PBLK (Airline A) hours\minutes	ABLK (Airline A) hours\minutes	ABLKS (Airline A) hours\minutes
4	11	0	0	4:20	4:04	16	4:22	4:11	11
4	20	0	0	4:15	3:48	27	4:16	4:00	16
11	4	0	0	4:05	3:49	16	3:58	3:58	0
20	4	17	6	3:50	3:52	-2	3:47	3:58	-11

Table 2-3: Average arrival delay, PBLK, ABLK, and ABLKS for common arcs on July 8, 2006

Origin Airport Index	Dest Airport Index	Avg. Arrival Delay (Airline B) minutes	Avg. Arrival Delay (Airline A) minutes	PBLK (Airline B) hours\minutes	ABLK (Airline B) hours\minutes	ABLKS (Airline B) hours\minutes	PBLK (Airline A) hours\minutes	ABLK (Airline A) hours\minutes	ABLKS (Airline A) hours\minutes
3	4	8.6	10	1:10	1:07	3	1:20	1:35	-15
4	3	7.4	0	1:10	1:05	5	1:26	1:22	4
4	11	2	2.3	4:20	4:19	1	4:22	4:15	7
4	20	0	4.5	4:15	3:53	22	4:09	4:09	0
11	4	0	36.7	4:05	3:46	19	3:56	4:13	-17
20	4	28	0	3:50	3:35	15	3:49	3:44	5

Table 2-4: Average arrival delay, PBLK, ABLK, and ABLKS for common arcs on July 12, 2006

2.3.3 Ground Delay Programs

The goal of Ground Delay Programs (GDP) is to control air traffic volume to airports where the projected traffic demand is expected to exceed the airport's acceptance rate for a lengthy period of time. Lengthy periods of such instances are normally a result of the airport's acceptance rate being reduced by external factors. The most common reason for a reduction in acceptance rates is inclement weather, such as low ceilings and visibility. GDPs work as follows: Flights that are destined to the affected airport are issued Controlled Departure Times (CDTs) at their point of departure. Flights that have been issued CDTs cannot depart until their assigned CDT. CDTs are calculated in such a way as to meter the rate that traffic arrives at the affected airport; ensuring that demand is equal to the acceptance rate. The length of delays that result from the implementation of a GDP is a factor of two things: (1) how much greater than the acceptance rate the original demand was, and (2) for what length of time the original demand is expected to exceed the acceptance rate (FAA [15]).

Metron Aviation provided GDP data for all the GDPs from April 1, 2007 to March 31, 2008. According to that, the percentages of airports that have GDPs for Airline A and Airline B are 39% and 27%, respectively. Moreover, one of the major hubs of Airline A had the highest number of issued GDPs (approximately 190) between 2007 and 2008 among all airports with ground holds. This implies a GDP was issued basically every other day at this airport with an average actual GDP length of 505 minutes. On average, Airline A has the largest share of traffic (roughly 53%) among all airlines with flights into and/or out of this airport (BTS (2006) [4]). The total number of issued GDP's between 2007 and 2008 was 218 at Airline A's major hubs and only 31 at Airline B's major airports. These statistics, together with the analysis above, begin to explain why Airline A tends to add more slack into its turn time than does Airline B.

2.3.4 Explanations of Planned Differences among the Airlines in Scheduling Slack Time

We speculate the major reason for Airline A to have a higher average PTT and lower average PBLK compared to Airline B has to do with the hub choices of Airline A. The three major hubs for Airline A are very busy airports with high traffic levels. When bad weather occurs, flights planned to arrive in these affected airports are subject to GDPs to ensure that demand for runway capacity does not exceed the reduced amount available in bad weather. Most of the low-cost carrier's major airports are not frequently impacted by GDPs, while the hubs of Airline A are often impacted. Further, as a legacy network carrier, Airline A performs a hub-and-spoke operation, which means a significant percentage of its flights will either fly out or into its hubs. Additionally, Airline A operates two banked hubs where a set of arriving flight legs are scheduled closely with a set of departing flight legs to allow timely passenger connections between arriving and departing flight legs. Delayed flight legs cause downstream delays to aircraft, crews and passengers, resulting in growing flight delays and cancellations as the day progresses. Under these conditions, it is an effective strategy for Airline A to plan a higher average turn time because ground slack can reduce departure delays caused by late incoming flights (i.e., propagated delays) at its major hubs. Block time slack, however, is not effective in getting aircraft back on schedule at airports that frequently implement ground holds. To do so, given average durations of 505 minutes for GDPs, would require exorbitant and impractical amounts of slack to be included in the planned block times. Airline B, which tends to fly into busy airports less frequently and has fewer airports subject to ground delay programs, however, faces a different situation. Adding more slack to its block times becomes a more effective strategy than placing slack in ground times because block time slack for improve on-time arrival performance.

2.3.5 Peaking vs. De-peaking

In a de-peaked schedule, aircraft need not wait on the ground for connecting passengers and can therefore save turn time, which can lead to increased aircraft utilization. Additionally, de-peaked schedules are more robust in the sense that demand for airport capacity, at least on the part of the airline operating the de-peaked schedule, is spread more evenly in time and its maximum is much less than that of a peaked schedule. Hence, reductions in capacity can have less impact on de-peaked than peaked schedule. Later analysis in this thesis shows that Airline A has only one de-peaked hub and two peaked schedules. Airline B, however, has de-peaked schedules at all of its major airports. Airline B, then, has shorter turn times and higher aircraft productivity. Airline A, however, must schedule longer ground turn times to "catch" banks at the hubs and to allow adequate time for arriving passengers to connect between flights. As indicated by the positive differences between ATT and PTT in Figure 2-5 and Figure 2-6, this slack did not serve as a buffer. The most plausible reason is that flights were delayed in departure due to the airlines' own problems, NAS, or security issues.

Chapter 3

Flight Delays and Cancellations

3.1 Introduction

Flight on-time performance has a direct impact on passenger delays. In this chapter, we compare flight delays and cancellations of the legacy carrier to those of the low-cost carrier on July 8, and July 12, in 2006. The flight delay analysis presented in this chapter also helps explain the differences between the two airlines in scheduling practices (discussed in Chapter 2) and passenger delays (to be discussed in Chapter 5). In Section 3.2, we compute and analyze flight performance statistics using information from the BTS data. In Section 3.3, we quantify the sources of delays; i.e., whether a flight delay was due to late incoming aircraft or due to other reasons.

3.2 Information of Flight Performance from the BTS Data

3.2.1 Flight Performance Statistics

Based on information from ASQP (BTS (2006) [5]), we compute the flight performance statistics for Airline A and Airline B on July 8, 2006 and July 12, 2006 (shown in Table 3-1). Our analysis is restricted to jet-operated flight legs because ASQP includes only jet-operated flight leg information.

	Airline A (07/08/2006)	Airline B (07/08/2006)	Airline A (07/12/2006)	Airline B (07/12/2006)
Number of flight operations (domestic U.S.)	**727**	**2698**	**922**	**3116**
15-minute on time performance (*15-OTP*)	**87.60%**	**89.00%**	**60.60%**	**75.80%**
Percentage of delayed flights* (only flights operated)	**12.40%**	**11.00%**	**39.40%**	**24.20%**
Percentage of cancelled flights	**0**	**0.44%**	**1.52%**	**0.89%**
Average delay of operated flights (minutes)	**6.36**	**4.82**	**38.75**	**12.28**
Average delay of flights with positive delays (minutes)[3]	**19.36**	**17.5**	**67.16**	**25.74**

* Delayed flights are the flights with delays greater than 15 minutes

Table 3-1: Flight delay statistics based on ASQP

From Table 3-1, we observe the following for July 8, 2006:

- Airline B operated 3.7 times more domestic flights than Airline A.
- Airline A and Airline B achieved comparable 15-OTP.
- Airline A had no cancellations while Airline B had 0.44% of flights cancelled.
- The average delay of Airline A's operated flights (6.36 minutes) was higher than that of Airline B's operated flights (4.82 minutes).
- The percentage of Airline A's delayed flights (12.40%) was higher than that of Airline B's delayed flights (11.00%).
- For flights that experienced positive delays, the average delay for Airline A was slightly higher than that for Airline B.

[3] The average flight delay (only for flights that experienced positive delays) for Airline A was 41.52 minutes and for Airline B 8.0 minutes in July 2006.

For July 12, 2006, we observe the following:

- Airline B operated 3.4 times more domestic flights than Airline A.
- Both airlines had worse performance than that on July 8, 2006.
- Compared to July 8, the numbers of flight operations were increased by a factor of 1.27 for Airline A and 1.15 for Airline B, respectively.
- Airline B achieved a higher 15-OTP than Airline A.
- The average delay of Airline A's operated flights was 3.16 times higher than that of Airline B's operated flights.
- The percentage of Airline A's delayed flights (39.40%) was higher than that of Airline B's delayed flights (24.20%).
- For flights that experienced positive delays, the average delay for Airline A was 2.61 times higher than that for Airline B.
- Compared to July 8, the average delay of flights with positive delays was increased by a factor of 3.47 for Airline A and a factor of 1.47 for Airline B.
- The percentage of delayed flights was increased by a factor of 3.18 for Airline A and 2.18 for Airline B.

3.2.2 Causes of Flight Cancellations and Delays

This section investigates the causes of flight delays and cancellations, using the U.S. DOT's definition. In Chapter 1, we present the DOT-defined causes of flight delays as: carrier delay, extreme weather delay, national aviation system (NAS) delay, security delay, and late arriving aircraft delay. In the ASQP data, the amount of delay attributed by each of the above-mentioned causes is reported. For example, a flight with a total arrival delay of 107 minutes has 32 minutes delay attributable to carrier delay, 4 minutes attributable to NAS delay, and 71 minutes attributable to late aircraft delay.

With such information, we compute the percentage of arrival delay attributed by each cause. In Figure 3-1, we depict these percentages for Airline A on July 8 and July 12, respectively. In Figure 3-2, we depict these percentages for Airline B on July 8 and July 12, respectively (BTS (2006) [5]).

On the "high-delay" day of July 12, we find extreme weather problems contributed 8% of the total arrival delay to Airline A's operation while only 4% to Airline B's operation. By comparing the amount of delay attributed to extreme weather conditions to the amount of total departure delay and arrival delay, respectively, we conclude that departure delays represented 90.03% of the total delay caused by extreme weather in Airline A's system. In other words, the extreme weather conditions resulted in GDPs that kept aircraft on the ground, delaying departures, at departure airports. Moreover, one hub in Airline A's network contributed 94.14% of the total delays caused by weather and 74.04% of the total departure delays caused by weather. A distinction between the two airlines is that Airline A suffered almost three times more NAS delay than Airline B. On July 12, NAS delay accounted for nearly half of the total delay in Airline A's system. NAS delay is a mixed result of non-extreme weather conditions, airport operations, heavy traffic volume, air traffic control, etc. We think the difference in NAS delay is attributable to the fact that Airline A has a significant percentage of flights flying into or out of congested hubs that are often affected by weather conditions and GDPs.

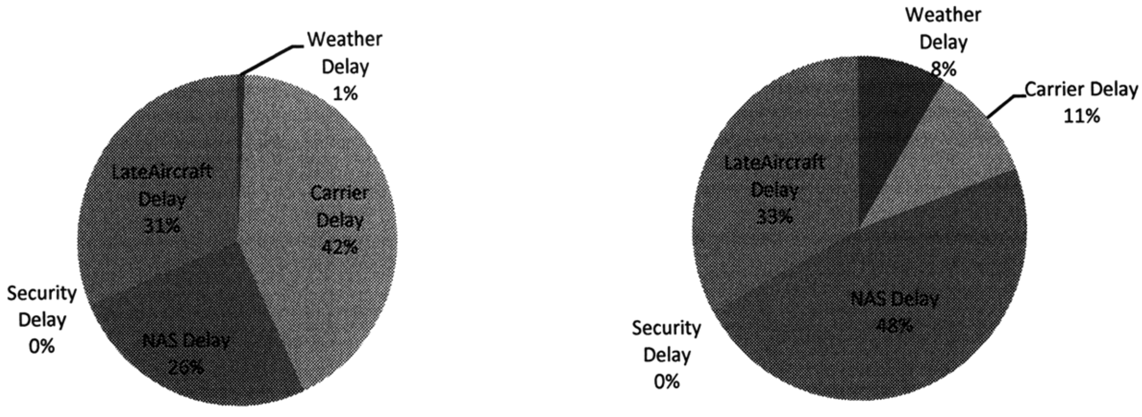


Figure 3-1: Causes of flight delay for Airline A on July 8 (left) and July 12 (right) in 2006

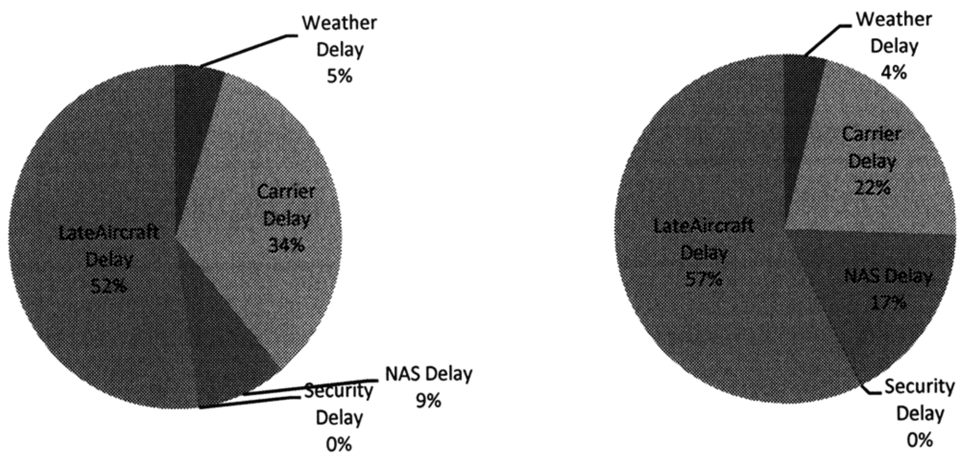


Figure 3-2: Causes of flight delay for Airline B on July 8 (left) and July 12 (right) in 2006

Also on the "high-delay" day, out of the fourteen flight cancellations of Airline A, seven of them (half of the cancellations) were due to weather problems at four airports. Of these seven cancelled flights due to weather problems, there were four departures from a single hub. All cancellations of Airline B, however, arose from carrier problems rather than weather.

3.2.3 Weighted 15-OTP Arrival Rates

Table 3-2 provides rankings of the 15-OTP arrival performance over all US airlines by major airports in July 2006, reported by the BTS [5]. We compute the percentage of flights in Airline A's and Airline B's networks based on their respective T-100 Segment data, which contains information regarding the total number of flight departures performed in each month and the origin/destination airports of these flights. We then multiply these percentages of flights by the 15-OTP rates in Table 3-2 to obtain weighted 15-OTP rates at each major airport for Airline A and Airline B (Table 3-3 and Table 3-4). We then make the following observations:

- Airline A has approximately 80% of its flights operating at the 31 busiest US airports. T-100 segment data reports that Airline A schedules and performs flight operations at all 31 airports.
- Airline B has only approximately 50% of flights operating at the 31 busiest US airports. T-100 segment data reports that Airline B schedules and performs flight operations at only 16 of the 31 airports.
- The sum of the weighted 15-OTP for Airline A is 70% and for Airline B is 75%. The overall 15-OTP arrival performances of the two airlines in July 2006, respectively, are 69% for Airline A and 77.7% for Airline B, according to Air Travel Consumer Report [13]. Airline A's performance can therefore, be estimated as a function of the performance at the major airports at which it operates. Airline B's performance, however, is better than that of the major

airports at which it operates. Hence, Airline A's reliability is impacted to a greater extent by changes in capacity and demand at the major airports.

Rank	July 2006	%
1	Salt Lake City, UT (SLC)	85.05
2	Cincinnati, OH (CVG)	82.00
3	Minneapolis/St. Paul, MN (MSP)	80.90
4	Dallas/Ft.Worth, TX (DFW)	80.54
5	Oakland, CA (OAK)	79.52
6	Denver, CO (DEN)	78.97
7	Phoenix, AZ (PHX)	78.80
8	Los Angeles, CA (LAX)	77.38
9	Detroit, MI (DTW)	76.83
10	San Diego, CA (SAN)	76.70
11	San Francisco, CA (SFO)	76.39
12	Orlando, FL (MCO)	75.71
13	Las Vegas, NV (LAS)	75.09
14	Chicago, IL (MDW)	74.55
15	Fort Lauderdale, FL (FLL)	74.17
16	Baltimore, MD (BWI)	74.11
17	Tampa, FL (TPA)	73.09
18	Houston, TX (IAH)	73.01
19	Atlanta, GA (ATL)	72.95
20	Charlotte, NC (CLT)	72.60
21	Seattle, WA (SEA)	72.57
22	Miami, FL (MIA)	70.37
23	Washington, DC (DCA)	70.19
24	Chicago, IL (ORD)	69.44
25	Boston, MA (BOS)	68.51
26	Washington, DC (IAD)	67.67
27	Pittsburgh, PA (PIT)	67.40
28	Philadelphia, PA (PHL)	64.19
29	New York, NY (JFK)	62.98
30	New York, NY (LGA)	59.94
31	Newark, NJ (EWR)	59.03

(Percent On-Time)

Table 3-2: Ranking of major airport on-time arrival performance in July 2006
Source: BTS, Airline On-Time Data

Airport	Flights	Flights %	OTP %	Weighted OTP %
SLC	92	0.43	85.05	0.36
CVG	1	0.00	82.00	0.00
MSP	136	0.63	80.90	0.51
DFW	326	1.52	80.54	1.22
OAK	91	0.42	79.52	0.34
DEN	422	1.96	78.97	1.55
PHX	333	1.55	78.80	1.22
LAX	783	3.65	77.38	2.82
DTW	184	0.86	76.83	0.66
SAN	364	1.69	76.70	1.30
SFO	481	2.24	76.39	1.71
MCO	614	2.86	75.71	2.16
LAS	520	2.42	75.09	1.82
MDW	94	0.44	74.55	0.33
FLL	449	2.09	74.17	1.55
BWI	215	1.00	74.11	0.74
TPA	383	1.78	73.09	1.30
IAH	7699	35.85	73.01	26.17
ATL	413	1.92	72.95	1.40
CLT	1	0.00	72.60	0.00
SEA	492	2.29	72.57	1.66
MIA	313	1.46	70.37	1.03
DCA	364	1.69	70.19	1.19
ORD	449	2.09	69.44	1.45
BOS	569	2.65	68.51	1.82
IAD	9	0.04	67.67	0.03
PIT	59	0.27	67.40	0.19
PHL	220	1.02	64.19	0.66
JFK	93	0.43	62.98	0.27
LGA	378	1.76	59.94	1.05
EWR	4930	22.95	59.03	13.55
Sum	**21477**			**70.08**
%	**0.80**			

Table 3-3: Weighted major airport on-time arrival performance in July 2006 of Airline A

Airport	Flights	Flights %	OTP %	Weighted OTP %
SLC	1293	2.75	85.75	2.36
SAN	2756	5.87	81.68	4.79
FLL	1273	2.71	80.32	2.18
LAX	3481	7.41	80.23	5.95
OAK	4111	8.75	79.44	6.95
TPA	2183	4.65	78.68	3.66
DTW	461	0.98	77.41	0.76
DEN	683	1.45	76.46	1.11
MCO	2858	6.09	76.41	4.65
SEA	1197	2.55	76.36	1.95
PHX	6093	12.98	75.80	9.84
PIT	619	1.32	73.55	0.97
BWI	5004	10.66	73.49	7.83
LAS	6753	14.38	72.33	10.40
MDW	6215	13.23	67.29	8.91
PHL	1979	4.21	64.21	2.71
Sum	**46959**			**75.01**
%	**0.50**			

Table 3-4: Weighted major airport on-time arrival performance in July 2006 of Airline B

3.3 Independent Delay and Propagated Delay

We classify all flight delay into the following two types of delay:

- *Propagated Delay* is flight delay caused by waiting for incoming aircraft. This delay is a function of an aircraft's routing. Late arriving aircraft is the sole cause of propagated delay. In Figure 3-1 and Figure 3-2, we show that propagated delay on July 8 (July 12) accounts for approximately 31% (33%) of total arrival delay for Airline A, and 52% (57%) of the total arrival delay for Airline B.
- *Independent Delay* is flight delay caused by all reasons other than delay propagation[4]. In Figure 3-1 and Figure 3-2, we show that independent delay on July 8 (July 12) accounts for approximately 69% (67%) of total arrival delay for Airline A, and 48% (43%) of the total arrival delay for Airline B.

Notice in Figure 3-1 and Figure 3-2, on July 8 and July 12, only 45% and 49% of independent arrival delays propagated to downstream flights for Airline A (i.e., translated into propagated delay), respectively. For Airline B, 100% of independent arrival delays[5] propagated to downstream flights on both days.

---

[4] Air carrier delay, extreme weather delay, NAS delay, and/or security delay cause independent delay. In particular, airport congestion affects the degree of independent delay of arrivals, while carrier delays, adverse weather conditions, airport operations, heavy traffic volume, and/or air traffic control affects the degree of independent delay of departures.

[5] Note on both days the percentages of delayed aircraft (52% and 57%, respectively) were greater than the sum of percentages of weather delay, carrier delay, NAS delay, and security delay (48% and 43%, respectively)

3.3.1 Computation of the Independent and Propagated Delay

Lan, Clarke, and Barnhart (2006) [20] have developed a way to compute propagated delays and independent delays. Figure 3-3 illustrates the concepts of propagated delays (PD) as well as independent arrival delays (IAD) and independent departure delays (IDD). The formulas are provided in Table 3-5.

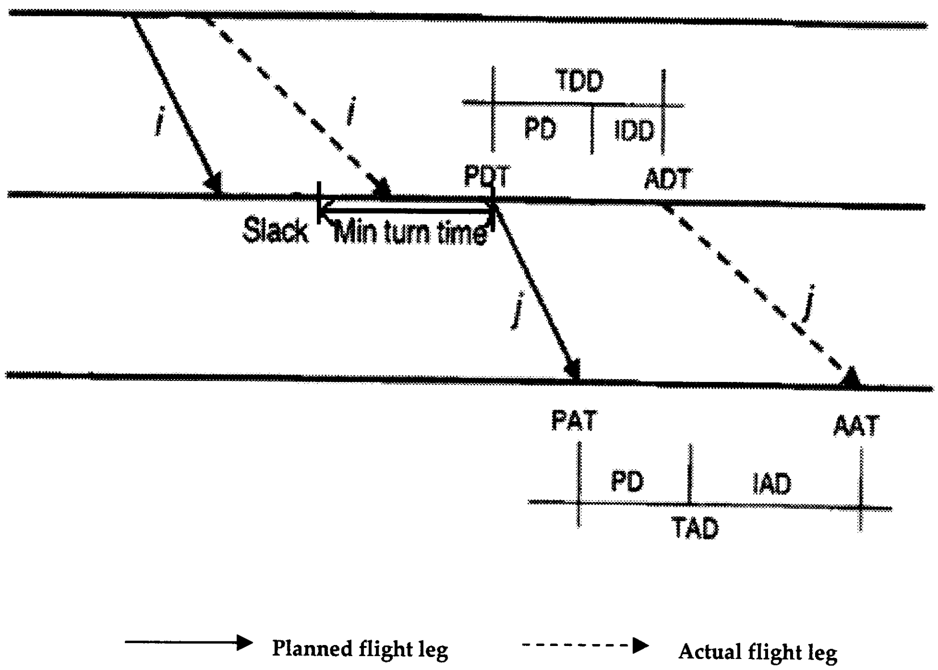


Figure 3-3: Scheme for computing PD, IDD, and IAD

Notations:

- TDD: Total Departure Delay
- PDT: Planned Departure Time
- ADT: Actual Departure Time
- TAD: Total Arrival Delay
- PAT: Planned Arrival Time
- AAT: Actual Arrival Time
- PD_{ij}: Propagated Delay of flight j due to flight i
- IDD: Independent Departure Delay
- IAD: Independent Arrival Delay
- MTT_{ij}: Minimum Turn Time between flight i and flight j (aircraft type dependent)
- $Slack_{ij}$: Slack planned into ground turn time between flight i and flight j
- PTT_{ij}: Planned Turn Time between flight i and flight j

$$PTT_{ij} = PDT_j - PAT_i$$

$$Slack_{ij} = PTT_{ij} - MTT = PDT_j - PAT_i - MTT_{ij}$$

$$TAD_i = AAT_j - PAT_i$$

$$\begin{aligned} PD_{ij} &= MAX\ (TAD_i - Slack_{ij}, 0) = MAX\ (AAT_i - PAT_i - PDT_j + PAT_i + MTT_{ij}, 0) \\ &= MAX\ (AAT_i + MTT_{ij} - PDT_j, 0) \end{aligned}$$

$$IDD_j = TDD_j - PD_{ij}$$

$$IAD_j = TAD_j - PD_{ij}$$

Table 3-5: Formulas for computing Slack, PD, IDD, and IAD

Our approach in this study will consist of four major steps:

1. Compute the Slack, PD, IDD, and IAD of each flight segment recorded in ASQP. This procedure will be applied to both Airline A and Airline B. A useful technique, tail number tracing, is described as follows:
    a) Group flights with the same tail number (indicating the same aircraft).
    b) For each group, sort the flights by PDT from the earliest scheduled to the latest scheduled and then apply formulas provided in Table 3-2 to each group.
2. Compute and compare the average PD, IDD, and IAD of all flights operated in Airline A's and Airline B's systems, respectively.
3. For each airline, compute the contribution (percentage) of IDD and IAD from each airport and identify the airports that are major sources of delays in this system.
    - The total IDD of an airport is the sum of IDD for each flight leg that departs the airport.
    - The total IAD of an airport is the sum of IAD for each flight leg that arrives at the airport.
    - The total PD of an airport is the sum of PD for each flight arriving at and departing the airport.
4. For each airline, compute the average IDD and IAD at each airport and compare these average delays among airports in the system.
    - The average IDD of an airport is the sum of IDD for each flight leg that departs the airport divided by the total number of flight legs departing the airport.

- The average IAD of an airport is the sum of IAD for each flight leg that arrives at the airport divided by the total number of flight legs arriving at the airport.

3.3.2 PD, IDD, and IAD Results

Table 3-6 displays the average PD, IDD, IAD, and the percentage of flights experiencing delay propagation for Airline A and Airline B, respectively.

AVERAGE	PD (minutes)	IDD (minutes)	IAD (minutes)	Total Number of Flights	Number of Flights with PD	Percent of Flights with PD
Airline A (07/08/06)	1.58	5.1	3.48	727	25	3.4%
Airline A (07/12/06)	12.48	20.65	25.43	922	121	13%
Airline B (07/08/06)	2	4.74	1.83	2686	188	7%
Airline B (07/12/06)	6.19	7.27	4.63	3116	580	18.7%

Table 3-6: The average PD, IDD, and IAD (in minutes)

Note the average IDD and IAD of Airline A are significantly greater than those of Airline B on July 12, 2006, the "high-delay" day. Moreover, IDD plus IAD are together more than triple the propagated delay for Airline A on that day. For Airline B, IDD plus IAD is almost double that of PD. Airline A experienced twice as much average PD as Airline B on July 12; however, the percentages of flights experiencing delay propagation were higher for Airline B than for Airline A on both days. The fact that Airline A had a smaller percentage of flights experiencing delay propagation but greater average propagated delay on the "high-delay" day perhaps has to do with its airport choices and hub-and-spoke operation; in particular, Airline A has a higher percentage of flights connecting at busy airports and two of its major hubs are located where bad weather can often reduce airport capacity and affect flight take-off and landings. Therefore, when bad weather occurs, flights into these locations are delayed by ground holds, while most of Airline B's major airports are not as prone to delays. When delays occur at Airline A's airports, the delay that propagates to downstream flights is likely to be larger than that of Airline B. More flights experience delay propagation for Airline B because there is little turn time slack in its operation and an arrival delay is likely to propagate to the next flight, unlike Airline A, which has relatively more turn time slack.

The following section quantifies the amount of delay contributed by the major airports of Airline A and Airline B, respectively.

3.3.3 IDD, IAD, and PD Results by Airport

In this section, we present delay statistics by airport for each airline and then compare average delay per aircraft at the major airports of Airline A and Airline B. Figures 3-4 to 3-7 display IDD, IAD and PD by airport for both airlines. We index airports of Airline A from 1 to 54 and airports of Airline B from 1 to 60. For Airline A, hub airports are 1, 5, and 26. For Airline B, "hub" airports are 1, 5, 7, 9, and 14. Evaluating IDD and IAD by airport provides useful information regarding the total independent delays contributed by each airport in an airline's network. We also compare the average delay per aircraft at the major airports of Airline A and Airline B (Table 3-7).

Statistics by Airport for July 8, 2006

For Airline A, the airport with the largest values of IDD, IAD, and PD was one of the airline's hubs. In particular, that hub contributed 62.55% of the total IDD, 49.91% of the total IAD, and 49.48% of the total PD to the entire system.

For Airline B, the airport with the largest values of IDD, IAD and PD is also one of the airline's "hubs". Specifically, this "hub" contributed 12.67% of the total IDD, 14.76% of the total IAD, and 7.42% of the total PD. Another major airport of Airline B contributed the second largest percentage of IDD (9.75%) and PD (7.09%) to the entire system and only 3.75% of IAD. A third airport in Airline B's network contributed 9.4% of IDD, 12.87% of the IAD, and 6.32% of the PD to the entire system. Interestingly, these 3 airports contributed far less, percentage-wise, of the system-wide IDD, IAD, and PD than does a single airport in Airline A's network.

Statistics by Airport for July 12, 2006

For Airline A, 44.95% of IDD, 42.59% of IAD, and 42.69% of PD came from its three hubs. In particular, to the entire system, one hub contributed 20.09% of the total IDD, 22.36% of the total IAD, and 34.25% of the total PD; a second hub contributed 16.37% of the total IDD, 13.97% of the total IAD, and 4.48% of the total PD; and the third hub contributed 8.49% of the total IDD, 6.26% of the total IAD, and 3.95% of the total PD.

For Airline B, 36.81% of IDD, 39% of IAD, and 25.38% of PD came from four airports. In particular, to the entire system, one airport contributed 15.69% of the total IDD, 24.35% of the total IAD, and 8.59% of the total PD; another contributed 12.85% of the total IDD, 8.22% of the total IAD, and 5.92% of the total PD; a third contributed 6.61% of the total IDD, 7.35% of the total IAD, and 2.33% of the total PD; and the fourth contributed 8.27% of the total IDD, 6.43% of the total IAD, and 10.87% of the total PD.

Observations from the Statistics

On July 8, 7 (4) airports accounted for 100% (80%) of the PD in Airline A's network while 57 (23) airports accounted for the PD in Airline B's network. On July 12, 37 (12) airports accounted for 100% (80%) of the PD in Airline A's network while 60 (27) airports accounted for the delay in Airline B's network. We believe the fact that Airline B has delay propagation spread among many more airports than Airline A is due to Airline B's scheduling practice of limiting turn time slack.

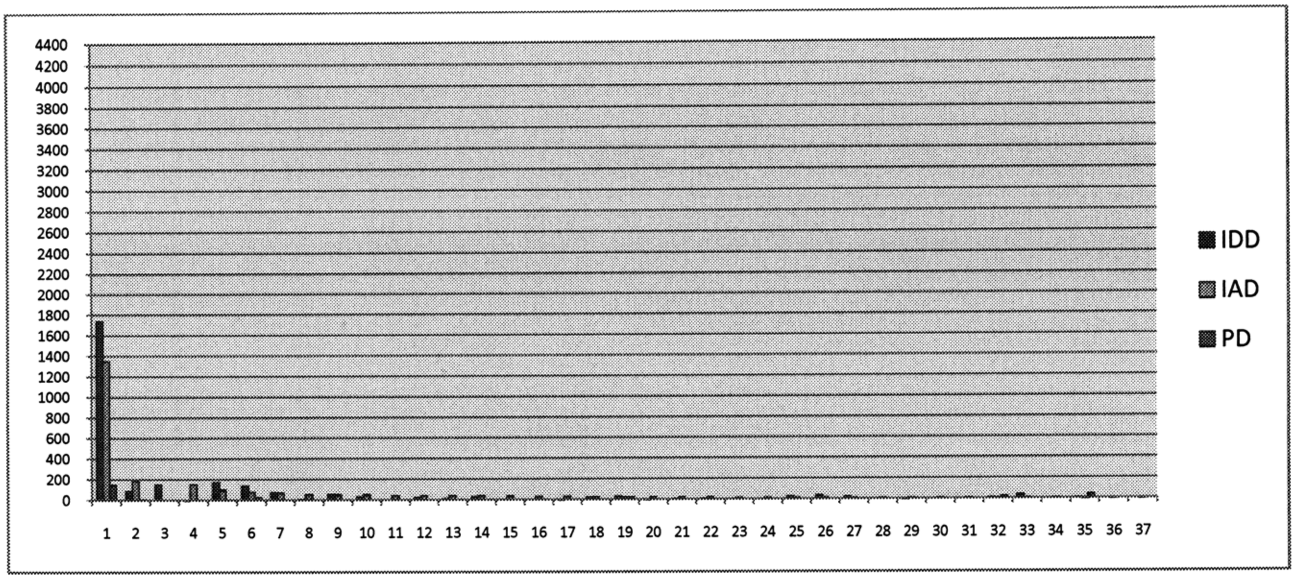


Figure 3-4: Airline A (07/08/2006): IDD, IAD, and PD by airport

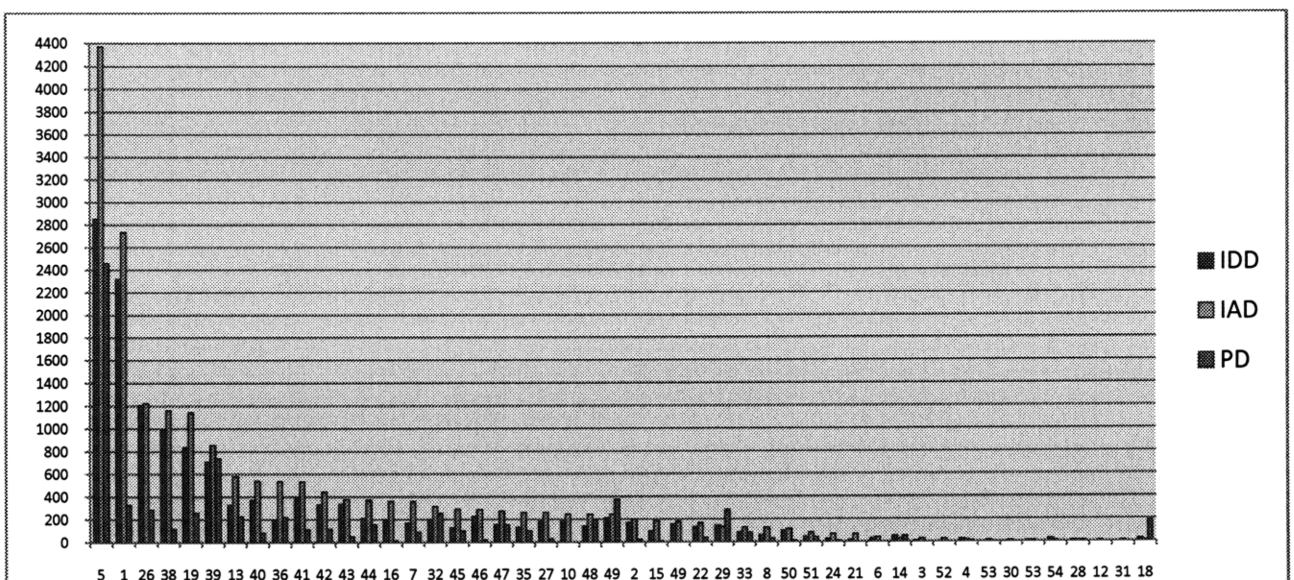


Figure 3-5: Airline A (07/12/2006): IDD, IAD, and PD by airport

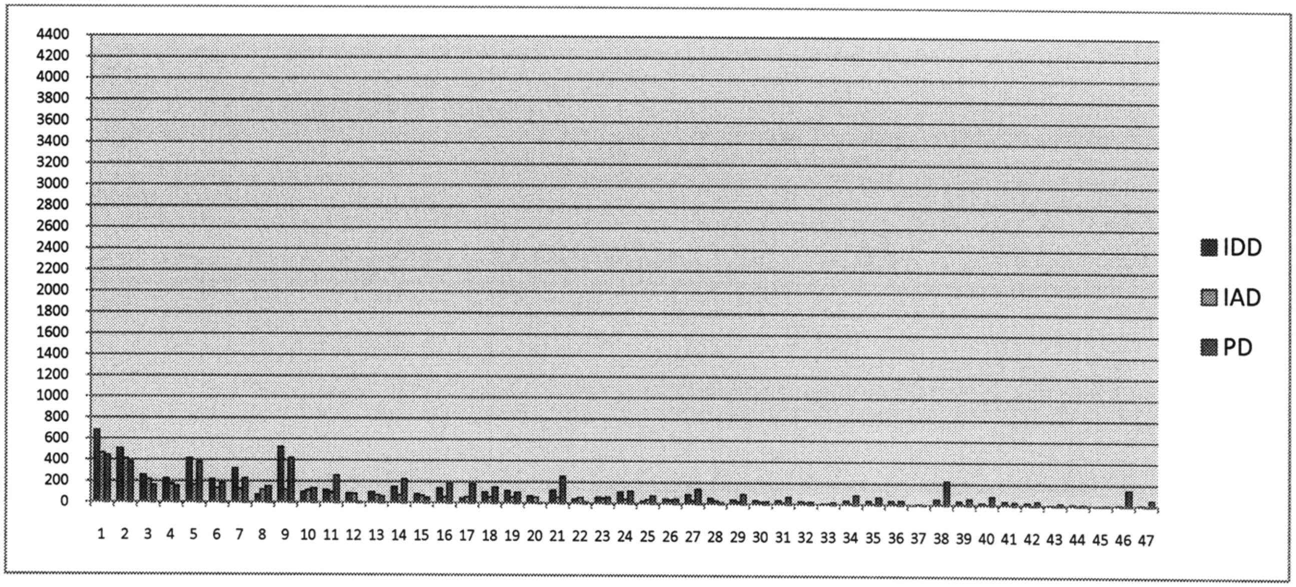


Figure 3-6: Airline B (07/08/2006): IDD, IAD, and PD by airport

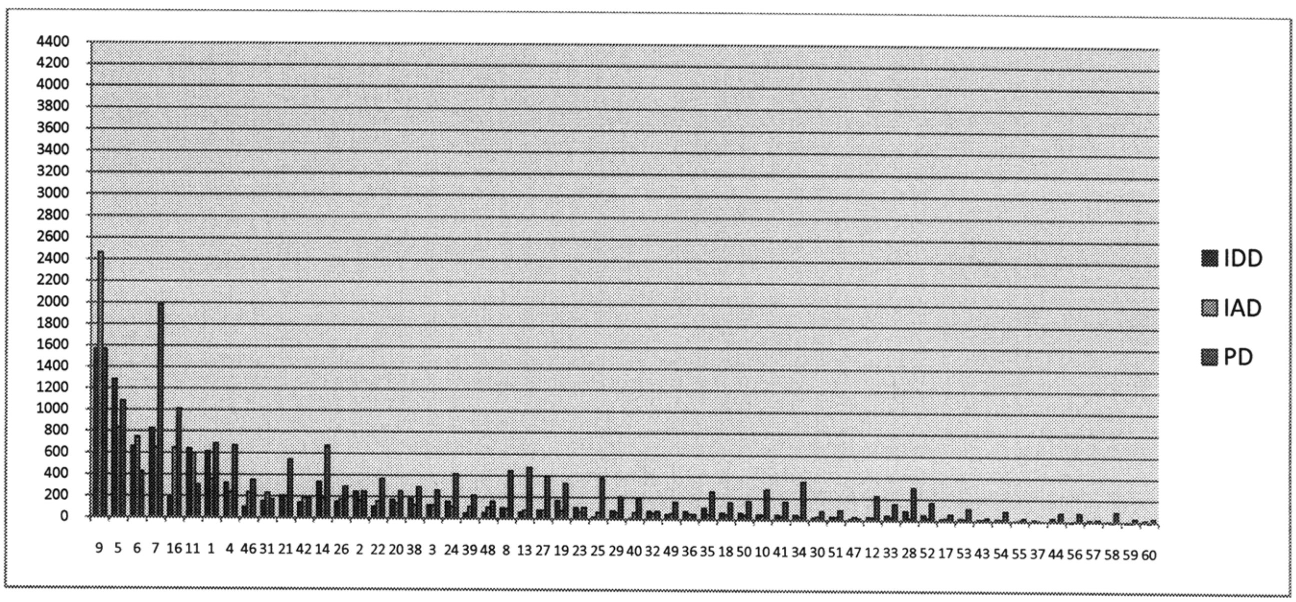


Figure 3-7: Airline B (07/12/2006): IDD, IAD, and PD by airport

Comparison of Average PD, IAD, and IDD Statistics for Both Airlines

As the above statistics indicate, for both airlines, the majority of IDD, IAD, and PD were contributed by their major airports, as expected. However, when the airport delay statistics are normalized by the number of flight operations at that airport, as shown in Table 3-7, we find that the magnitudes of independent delay per flight were much less for the major airports of Airline B than for those of Airline A on July 12. For instance, IDD (IAD) per flight was 17.17 minutes (27.66 minutes), 8.96 minutes (10.5 minutes), and 28 minutes (27.18 minutes) for the three major hubs of Airline A, respectively. IDD (IAD) per flight was only 5.81 minutes (3.76 minutes), 7.53 minutes (11.85 minutes), 3.05 minutes (0 minutes), 5.01 minutes (3.92 minutes), and 2.47 minutes (1.37 minutes) for the five major airports of Airline B, respectively.

We also compute the average IDD, IAD, and PD per flight over Airline A's three major hubs and Airline B's five major "hubs" on July 12, as follows.

July 12, 2006	IDD	IAD	PD
Hub average (Airline A)	13.77	17.98	6.62
"Hub" average (Airline B)	4.96	4.81	6.41
Ratio (Airline A/Airline B)	2.78	3.74	1.03

Airline A experienced 2.78 (3.74) times more average IDD (IAD) per flight over its three major hubs than did Airline B. Airline A had a slightly higher average PD per flight over its three major hubs (1.03 times as much as Airline B's PD value). We believe this difference resides in the fact that Airline A has a significant percentage of flights flying into or out of hubs with high congestion. Because independent delays can often be attributed to airport congestion, higher NAS delays mean higher degrees of congestion and hence, more independent delays. As shown in 3.2.2, NAS delay accounted for nearly half of total delay in Airline A's network, while it accounted for only 17% in Airline B's network on July 12, 2006.

We also compute the changes in IDD, IAD, and PD per flight (in minutes and percent) between July 8 and July 12 for both airlines. These results are displayed in Table 3-8. We find both independent delay and propagated delay at two hubs of Airline A are significantly greater on July 12, 2006, the "high-delay" day, than on July 8, 2006, the "low delay" day. In terms of absolute differences, Hub 2 had an increase of 15.81 minutes for IDD per flight, 26.89 minutes for IAD per flight, and 15.57 minutes for PD per flight on July 12. Hub 3 had an increase of 26.97 minutes for IDD per flight, 26.77 minutes for IAD per flight, and 6.31 minutes for PD per flight on July 12. In terms of changes in percent, the average IDDs per flight were increased by 1163% and 2618% for Hub 2 and Hub 3, respectively. The average IADs per flight were increased by 3492% and 6529% for Hub 2 and Hub 3, respectively. Because Hub 2 and Hub 3 had no PD on July 8, the changes in percent are undefined.

Between the "high-delay" day and "low-delay" day, the differences in independent delay and propagated delay of Airline B's three largest "hub" airports were on the order of one hundred[6], much less than those of Airline A's two hubs. "Hub" 1 of Airline B had an increase of 3.82 minutes for IDD per flight, 2.97 minutes for IAD per flight, and 3.07 minutes for PD per flight on July 12. "Hub" 2 of Airline B had an increase of 4.95 minutes for IDD per flight, 11.2 minutes for IAD per flight, and 5.23 minutes for PD per flight on July 12. "Hub" 3 of Airline B had a decrease of 0.78 minutes for IDD per flight, a decrease of 0.91 minutes for IAD per flight, and an increase of 0.86 minutes for PD per flight on July 12. In terms of changes in percent, the average IDDs per flight were increased by 193% and 192% for "Hub" 1 and "Hub" 2, respectively. The average

[6] except one instance of "Hub" 2 where the IAD per flight was increased by 1723%

IDD per flight was decreased by 20% for "Hub" 3. The average IADs per flight were increased by 372% and 1723% for "Hub" 1 and "Hub" 2, respectively. The average_IAD per flight was decreased by 34% for "Hub" 2. The average PDs per flight were increased by 170%, 228%, and 34% for "Hub" 1, "Hub" 2, and "Hub" 3, respectively.

The conclusion here is that between the "high-delay" day and "low-delay" day, the increases in independent delay and propagated delay of Airline B's three largest "hub" airports were much less than those of Airline A's two East Coast hubs.

Airline A	**Hub 1**		**Hub 2**		**Hub 3**	
Date	**7/8/2006**	**7/12/2006**	**7/8/2006**	**7/12/2006**	**7/8/2006**	**7/12/2006**
Average IDD	7.85	8.96	1.36	17.17	1.03	28
Average IAD	6.11	10.5	0.77	27.66	0.41	27.18
Average PD	0.64	1.24	0	15.57	0	6.31
Airline B	**"Hub" 1**		**"Hub" 2**		**"Hub" 3**	
Date	**7/8/2006**	**7/12/2006**	**7/8/2006**	**7/12/2006**	**7/8/2006**	**7/12/2006**
Average IDD	1.98	5.81	2.58	7.53	3.81	3.03
Average IAD	0.8	3.76	0.65	11.85	2.66	1.75
Average PD	1.81	4.88	2.29	7.52	2.51	3.37

Table 3-7: Average IDD, IAD, and PD per flight (in minutes)

Airline A	**Hub 1**		**Hub 2**		**Hub 3**	
Date	**Differences (min)**	**Change %**	**Differences (min)**	**Change %**	**Differences (min)**	**Change %**
Average IDD	1.11	14	15.81	1163	26.97	2618
Average IAD	4.39	72	26.89	3492	26.77	6529
Average PD	0.60	94	15.57	N/A	6.31	N/A
Airline B	**"Hub" 1**		**"Hub" 2**		**"Hub" 3**	
Date	**Differences (min)**	**Change %**	**Differences (min)**	**Change %**	**Differences (min)**	**Change %**
Average IDD	3.82	193	4.95	192	-0.78	-20
Average IAD	2.97	372	11.20	1723	-0.91	-34
Average PD	3.07	170	5.23	228	0.86	34

Table 3-8: The changes in IDD, IAD, and PD per flight between July 8 and July 12 for both airlines (in minutes and %)

Chapter 4

Passenger Demand and Delay Estimation

4.1 Literature Review

Using proprietary airline data, Barnhart and Bratu (2005) [3] developed a Passenger Delay Calculator (PDC) to investigate the impact of delayed flights, cancelled flights and missed connections on passenger trip time. They estimated that disrupted passengers, those who missed one or more of their connections, due to delayed flights, or with one or more of their flights cancelled, experienced an average delay that was about 20 times greater than the average flight delay in that same period. Their research quantified the gap between passenger delays and flight delays with real data, as well as demonstrated that flight based metrics alone are a poor proxy for passenger delays in hub-and-spoke airlines.

Ball, et al. (2005) [1] developed an analytical passenger delay model as part of the National Aviation Space (NAS) Strategy Simulator. The model is based on a decision tree which determines the probability of delayed flight leg, missed connection, cancelled flight leg, and on-time flight leg. A major limitation of their work is that they assume a fixed passenger delay (7 hours) for all the passengers experiencing missed connections or flight cancellations. This assumption assumes a homogenous transportation network and neglects airport and route specific characteristics.

Sherry and Wang (2007) [26] expanded Barnhart and Bratu's model to a national scale study with detailed analysis on various O-D pairs, departure and arrival airports, as well as load factor levels. Their model uses a large quantity of publicly accessible data and provided rankings of O-D pairs, airports and other results in the measure of passenger on-time performance. However, there are two major drawbacks in their research:

1. The algorithm assumes flights in peak hours have the same load factor as flights in non-peak hours and fails to use actual passenger enplanements and aircraft size to validate this assumption.
2. Unlike the PDC, Sherry and Wang's analysis considers only non-stop segment data and excludes the possibility of disruptions due to missed connections.

4.2 Contributions of Our Methodology

Our work uses the PDC algorithm to quantify passenger delays. However, one limitation of Bratu and Barnhart's research is that the PDC depends on the availability of detailed passenger booking data provided by airlines. In this research, we recognize that itinerary information and airline booking data are not generally accessible and therefore, we develop a method to determine passenger booking information for all scheduled flights using only data available from the BTS. Our method consists of two core parts:

- An algorithm that generates itineraries, and
- A linear integer programming formulation that computes the number of passengers on each of the generated itineraries.

To address the heterogeneity in passenger demand or load factors for different days of a week and different times of a day, we consider an airline's historical passenger booking profile for July 2000. Although far from being an accurate source to draw passenger demand profiles, this database serves our purpose of conducting a system-wide study and provides us an approximation of air-travelers' behavior across different days of a week and different times of a day for the major domestic markets.

The outline for this chapter is as follows: we first illustrate how to generate itineraries using the publicly accessible data from BTS; then, we discuss the linear integer programming formulation that allocates the passengers to our generated itineraries; last, we input the results of these steps to the PDC to compute passenger delay statistics. Figure 4-1 illustrates the framework of our Itinerary Generation Algorithm (IGA), Passenger Allocation Process (PAP), and Passenger Delay Calculator (PDC).

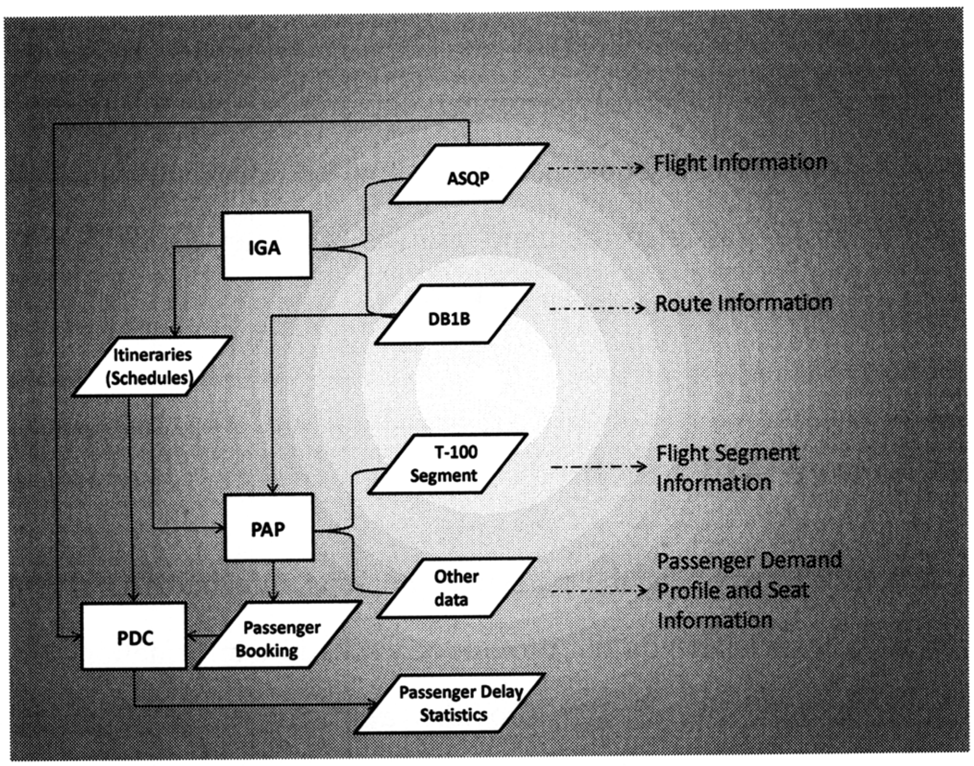


Figure 4-1: The framework of the Itinerary Generation Algorithm (IGA), Passenger Allocation Process (PAP), and Passenger Delay Calculator (PDC)

4.3 Data Descriptions

We use the publicly accessible data described in Chapter 1.6 to generate itineraries and allocate passengers so that "estimated" passenger booking information can be derived and input to our PDC for computing passenger delay statistics. DB1B provides only passenger route information (no flight schedule information) and ASQP provides only flight information (no passenger information). The FAA Aircraft Registry Database is used to obtain the flight seating capacity information, which is then applied to the PAP and the disruption recovery process in the PDC. In addition to data described in Chapter 1.6, an airline's historical passenger booking profile for July 2000 is also included. It provides passenger booking and no-show information for July 2000. We use this database to derive passenger demand profiles for different days of a week and different times of a day, which are input to the PAP.

4.4 The 3-Stage Approach

The major difficulty in utilizing the passenger booking information from BTS is that most of its data (such as DB1B) do not provide any schedule information but only route or market information. This chapter provides a model to strengthen the linkage between passenger booking information and flight schedules using public data. Given an O-D market in DB1B of a certain quarter, we look into the ASQP data (e.g. a 90-day span) in the same quarter and enumerate all possible flight combinations that serve this O-D pair using MCT and MLT as selection rules. It is relatively simple to build passenger itineraries by linking ASQP (detailed flight information) with DB1B (aggregated passenger booking information). Our model includes an algorithm that generates itineraries and a passenger allocation scheme that determines the passenger flow on each itinerary for every airline under study.

4.4.1 Itinerary Generation Algorithm (IGA)

Problem Description: Given a particular airline, construct its itineraries using publicly accessible data such as DB1B and ASQP.

Assumptions: In the following development, our itineraries will contain no more than two flight legs as the majority of domestic passengers make no more than two connections. Moreover, we only consider itineraries within a single airline at a time; in other words, itineraries operated by multiple airlines will not be generated. These restrictions can be lifted and our approach is still applicable; they are in place only to limit the number of itineraries generated that are likely to have no passengers.

Inputs to IGA include:

1) Aircraft routings (origin airports, connecting airports, if any, and destination airports) from DB1B. We will refer to the routings as O-T-D (*Origin-Transfer-Destination*) or O-A-D (*Origin-Absence of Transfer-Destination*) in the following discussion for simplicity.
2) Planned flight schedules from ASQP:
   a. PAT_i – Planned Arrival Time of flight i (available in ASQP data, Column "CRSArrTime")
   b. PDT_j – Planned Departure Time of flight j (available in ASQP data, Column "CRSDepTime")
3) User-Defined Parameters:
   a. *MLT* – Maximum Layover Time
   b. *PRT* – Passenger Ready Time

The steps of the IGA algorithm are illustrated below:

STEP 1: For each airline, identify the *O-T-D* airports served during a quarter from DB1B. *O-A-D* is used to indicate a local itinerary route. For instance, ATL-IAH-EWR is a connecting itinerary for the O-D pair ATL-EWR while ATL-A-EWR is a local itinerary for the O-D pair ATL-EWR. The *roundtrip* indicators in DB1B Ticket are used to separate coupons with round trips[7].

STEP 2: For each O-A-D or O-T-D identified in ***STEP 1***, construct the corresponding sequence of flight legs, or itineraries, from ASQP in a stepwise fashion, with the itineraries for O-A-D pairs served by non-stop flights constructed first, and the itineraries with two legs (O-T-D) constructed next. Discriminators such as Minimum Connecting Time (MCT) and non-stop market frequency can be used to determine whether a particular itinerary should be selected or not.

Itinerary Feasibility: Determining the feasibility of itineraries for each O-A-D or O-T-D for each airline requires the following sequential algorithm:

⇒ For each *O-A-D*,

- ➢ The flight leg's departure and arrival airports in ASQP correspond to the origin (O) and destination (D) airports in DB1B, respectively

⇒ For each *O-T-D*,

- ➢ The *first* flight leg's departure and arrival airports in ASQP correspond to the origin (O) and connecting (T) airports in DB1B, respectively;
- ➢ The *second* flight leg's departure and arrival airports in ASQP correspond to the connecting (T) and destination (D) airports in DB1B, respectively;
- ➢ The *second* flight leg departs later than the *passenger ready time* (PRT); that is, the time between the arrival of the *first* flight leg and the departure of

[7] Flight legs from an origin airport *o* to a destination airport *d* constitute a route, while the return flight legs from *d* to *o* represent a different route, called the opposite route.

the *second* flight leg in the itinerary must be no less than MCT (Minimum Connecting Time); and

- The time between the arrival of the *first* flight leg and the departure of the *second* flight leg in the itinerary must be no greater than MDT (Maximum Layover Time).

Suppose flight i serves as the first leg and flight j serves as the second leg

$$PRT = PAT_i + MCT \leq PDT_j.$$

Thus, $PAT_i + MCT$ will be used to select the second flight from ASQP in the IGA algorithm. A typical value for MCT is 15 minutes. However, because different airports require different connecting time, we set MCT based on the connecting airport. For instance, Chicago O'Hare connecting passengers may need 25 minutes to make a connection.

4.4.2 Passenger Allocation Process (PAP)

Problem Description: Given a particular airline, a particular day of the year, and a vector of O-D based passenger demands (quarterly aggregated), estimate the number of passengers transported on each itinerary. This requires allocating passenger flows to the itineraries generated by IGA. DB1B, a 10% sample of airline tickets from reporting carriers, provides counts of passengers transported on each O-D pair on a quarterly-basis. From this, we get estimates of the total number of passengers transported on an O-A-D or O-T-D itinerary daily, and then allocate these passengers to itineraries throughout the day using the T-100 information and passenger booking profiles. The T-100 segment database with its count of passengers transported on each non-stop flight segment on a monthly-basis is to constrain passenger allocations to match those observed in actuality.

Researchers have tried different approaches to tackle this problem. A typical way is to apply discrete choice models and quantify passengers' travel preferences, referred to as itinerary choice problems (Coldren et al. (2003) [12]). We develop a linear integer programming formulation to solve this problem. To the best of our knowledge, this has never been done by others. The basic idea is to minimize the deviation of estimated passenger flows and actual passenger flows subject to a set of flow constraints and a flight seating capacity constraint. This optimization-based approach has a major advantage in handling quantitative constraints associated with highly aggregated data, such as BTS data. Additionally, compared to most itinerary choice models, an optimization approach does not have to work at the level of individual observations and consequently, circumvents many data issues relevant to choice models. We describe the constraints, right-hand-side (RHS) parameters, and objective function in the following.

Notations

I: the set of itineraries generated by the IGA

R: the set of routes in DB1B

F: the set of operated flights in ASQP

S: the set of non-stop segments in T-100 segment data[8]

M: the set of O-D markets

P: the set of periods

[8] An element of S is the set of operated flights with the same origin and destination in F.

Constraint Set 1: *the flight seating capacity constraints*. The seating capacity for each flight in the airline's network can be derived using the following procedures:

a) Obtain the tail number of each of the airline's flights in ASQP and match the aircraft tail number to its aircraft type using the FAA Aircraft registry database [15].

b) After identifying aircraft types, obtain from the target airline's official website the seating capacity, denoted by T_f, for each flight f.

The PAP should assign passengers to itineraries in the way such that the flight seating capacity is never exceeded by the passenger flow on a plane.

Constraint Set 2: *the route passenger flow constraints*. A route can be either a local or connecting route. The right-hand-side (RHS) parameters are target values that we estimate from DB1B market data for a particular day d, and the particular airline, using the following procedures:

a) Aggregate the number of passenger bookings for the airline over coupons (DB1B Coupon) with the same O-T-D or O-A-D airports to obtain quarterly route passenger flow.

b) Obtain the percentage of annual passengers transported (by airline) for the month in which day d falls, using BTS data (2006) [4]. Divide this percentage by the sum of the percentages corresponding to the three months in the quarter containing day d.

c) Compute the relevant monthly route passenger flow by multiplying a) and b) and, to obtain the weekly average route passenger flow, divide this value by the number of weeks in that month.

d) Derive a weekly passenger demand profile, represented by the percentage of booked passengers that travel on each day of the week over a week, using an airline's actual historical passenger booking data. Multiply c) by the percentage corresponding to day d to obtain the daily route passenger flow for d, denoted by T_R.

The intuition behind the route passenger flow constraints is that passenger demand for an O-D route varies by day. Although procedure d) assumes different airlines have similar weekly passenger demand profiles, constraint set 1 enforces the assignment of passengers to match the daily seating capacity provided by the airline and the other constraint sets 2, 3 and 4, work to ensure that the assignment of passengers mimics the T-100 segment data.

Constraint Set 3: the *segment passenger flow constraints*. The total flow on a flight segment consists of local and/or connecting passengers. For example, assume the flight segment A-B has 100 passengers: 50 of these passengers connect at B and continue flying; the other 50 passengers, who might have connected or originated at A, have their final destination at B. The total number of passengers on a segment, that is the RHS target values, is derived from T-100 Segment data, using the following procedures:

a) Aggregate the number of transported passengers of the airline over its non-stop segments (T-100 Segment) with the same O-D airports to obtain the monthly segment passenger flow.
b) To obtain the weekly average segment passenger flow, we divide a) by the number of weeks in the month of day d.
c) Using the weekly passenger demand profile (i.e., a typical share of booked passengers on each day of a week) computed for constraint set 2, multiply the share on day d by b) to obtain the daily segment passenger flow, denoted by T_S.

Similar to the route passenger flow constraints, the segment passenger flow constraints are to match, as closely as possible, the assignment of passengers and the actual passenger demand on each segment s, estimated as T_s.

Constraint Set 4: *the period passenger flow constraints.* The RHS parameters represent the airline's passenger flow in each market, commencing in each period. A market is defined to be any O-D pair between which passengers travel. The RHS passenger flow parameters are derived from DB1B and an airline's historical data, using the following procedures:

a) Aggregate the number of passenger bookings for the airline over coupons (DB1B Coupon) in the same market to obtain quarterly market passenger flow.

b) Obtain the percentage of annual passengers transported (by airline) for the month in which day d falls, using BTS data (2006) [4]. Divide this percentage by the sum of the percentages corresponding to the three months in the quarter containing day d.

c) Compute the monthly market passenger flow for the airline by multiplying a) and b). To obtain the weekly average market passenger flow, divide the monthly flow by the number of weeks in that month.

d) Derive the weekly passenger demand profile (i.e., a typical share of booked passengers on each day of a week) using an airline's actual historical passenger booking data.

e) Multiply c) by d) to obtain the airline's daily market passenger flow for the particular day under investigation.

f) Derive a "time of day" passenger demand profile (i.e., the share of booked passengers for each non-overlapping, pre-defined period in a day) using an airline's historical passenger booking data. For our work, we define three periods: 0600-1200 (morning), 1200-1800 (afternoon), and 1800-2400 (evening).

g) Multiply e) by f) to obtain the market passenger flow for each period of a day. In other words, the period passenger flow is the product of the total passengers in a given market m on a particular day and the fraction of passengers in that market during period p. T_{MP} denotes period p passenger flow in market m.

When applying the above procedures, we find that connecting markets and local markets have different "time of day" passenger demand profiles (in other words, local and connecting passengers show different travel behavior).

The intuition behind the period passenger flow constraints is that passenger demand varies by time of day and different markets are likely to have different passenger demand profiles. For example, demand for a business market may peak at a different time of day compared to that of a leisure market. To approximate better the number of passenger bookings on each itinerary, we include these time-of-day considerations in our PAP.

The objective function attempts to minimize the sum of all slack or surplus variables, normalized by the corresponding target values (RHS parameters), i.e., the total deviation of all constraints. w's represent the "weights" , where $w_{r\_slack} = w_{r\_surplus} = 0.5$, $w_{seg\_slack} = w_{seg\_surplus} = 0.5$, $w_{sch\_slack} = w_{sch\_surplus} = 0.3$, and $w_{seat} = 0.5$. The weights reflect how close we want the left hand side values to match the right hand side parameters. Because the RHS of constraint set 4 is derived from an airline's historical passenger booking profile for July 2000, which has less accuracy than the other parameters, we assign a smaller weight to its corresponding slack and surplus variables in the objective function. The final weights are chosen based on a trial-and-error process.

The Optimization Model

Decision Variables[9]

$X_i \in \mathbf{Z}^+$: number of passengers assigned to itinerary i, where $i \in I$

$Route\_slack_r \in \mathbf{Z}^+$: slack variable for **each** route constraint r, where $r \in R$

$Route\_surplus_r \in \mathbf{Z}^+$: surplus variable for **each** route constraint r, where $r \in R$

$Seg\_slack_s \in \mathbf{Z}^+$: a non-negative slack variable for **each** segment constraint s, where $s \in S$

$Seg\_surplus_s \in \mathbf{Z}^+$: a non-negative surplus variable for **each** segment constraint s

$Period\_slack_{mp} \in \mathbf{Z}^+$: a non-negative slack variable for **each** period constraint mp, where $m \in M$, $p \in P$, and $mp \in M \times P$ (the cartesian product of M and P indicating market m during period p)

$Period\_surplus_{mp} \in \mathbf{Z}^+$: a non-negative surplus variable for **each** period constraint mp, where mp is defined the same as above

Indicator Parameters

1. $\delta_{ir} = 1$ if itinerary i corresponds to route r; 0 otherwise
2. $\varphi_{is} = 1$ if itinerary i contains segment s[10]; 0 otherwise
3. $\lambda_{if} = 1$ if itinerary i is served by flight f; 0 otherwise
4. $\eta_{i,mp} = 1$ if itinerary i serves market m and departs in period p; 0 otherwise
5. $\pi_r = 1$ if route r is a connecting route; 0 otherwise

[9] We solve the optimization problem for each airline and each day. For simplicity, the target values for that day are denoted without the index indicating the day. We also drop the index denoting the airline.
[10] Note a segment corresponds to the set of non-stop flights throughout the day with a given origin and destination.

Constraints[11]

(1) $\sum_{i \in I} \lambda_{if} x_i \leq T_f \; \forall f \in F;$

(2) $\sum_{i \in I} \delta_{ir} x_i + Route\_slack_r - Route\_surplus_r = T_r \; \forall r \in R;$

(3) $\sum_{i \in I} \varphi_{is} x_i + Seg\_slack_s - Seg\_surplus_s = T_s \; \forall s \in S;$

(4) $\sum_{i \in I} \eta_{i,mp} x_i + Period\_slack_{mp} - Period\_surplus_{mp} = T_{mp} \; \forall m \in M \; and \; p \in P.$

Objective Function

$$\begin{aligned}
\textbf{\textit{Minimize}}: \quad & \sum_{r \in R} \left(\frac{w_{r_slack} Route_slack_r}{T_r} + \frac{w_{r_surplus} Route_surplus_r}{T_r} \right) \\
& + \sum_{s \in S} \left(\frac{w_{seg_slack} Seg_slack_s}{T_s} + \frac{w_{seg_surplus} Seg_surplus_s}{T_s} \right) \\
& + \sum_{p \in P} \sum_{m \in M} \left(\frac{w_{mp_slack} Period_slack_{mp}}{T_{mp}} + \frac{w_{mp_surplus} Period_surplus_{mp}}{T_{mp}} \right)
\end{aligned}$$

We solve this optimization problem with CPLEX on OPL 5.0. The outputs include the number of passengers assigned to each itinerary generated in IAG, that is, an estimation of passenger booking information. These outputs are combined with the flight schedules from ASQP and input into the PDC to compute passenger delay statistics.

[11] Because the left hand side of the constraints is an integer matrix with linearly independent rows and the right hand side is an integer vector, by Unimodularity Theorem, there exists an integer optimal solution to the linear program version of this problem. Therefore, even though the problem is formulated as a linear integer program, it can be solved to optimality by its linear relaxation.

4.4.3 Passenger Delay Calculator (PDC)

Most of the following discussions are based upon the work of Stephane Bratu (2005) [3], who originally developed the PDC algorithm.

Definition of Disruptions. The core of PDC is to distinguish between disrupted and non-disrupted passengers, as well as to recover the disrupted passengers. As defined earlier, a passenger is *disrupted* if:

- One or more of the flights in his/her scheduled itinerary is canceled; or
- The passenger misses connections.

Consequently, disrupted passengers must be re-accommodated on alternative itineraries, while *non-disrupted* passengers have the same scheduled and actual itineraries. Because scheduled and actual itineraries are different for *disrupted* passengers, the set of passengers P can be divided into two mutually exclusive and collectively exhaustive subsets: D and ND, corresponding to the set of *disrupted* and *non-disrupted* passengers, respectively. We denote the queue of passengers to be re-accommodated by the airline at time t as $DQ(t)$ and let $DT(p)$ be the time of disruption for passenger p. Let $d(p)$ be the *Passenger Arrival Delay* for p, computed as the maximum of zero and the difference between p's actual arrival time and scheduled arrival time. Hence, $d(p) = max(AAT(L(p)) - PAT(L(p)); 0)$, where $L(p)$ denotes the last flight in p's actual itinerary, $(AI(p))$.

PDC Assumptions. PDC provides only *approximate* delay estimates. The assumptions underlying our PDC are likely to lead to underestimates of actual passenger delays. We present them in the following:

a. ***Perfect information***: we assume at any point in time that future operations are known exactly. Consequently, disrupted passengers, once they are assigned to recovery itineraries, cannot be disrupted again. Additionally, we assume in PDC that the airline has perfect knowledge of the number of seats available for each flight. In reality, airlines do not have this information, as some passengers might not show-up for their flights, especially business passengers who sometimes have fully refundable tickets.

b. ***Instantaneous information:*** we assume that a disrupted passenger is instantaneously rebooked on the best feasible recovery itinerary, that is, the one which arrives earliest at the disrupted passenger's destination, has an available seat, and has at least the minimum connect time between the passenger disruption time and the departure of the first flight in the recovery itinerary.

Regarding service priorities, based on current industry practices and available information, we have made the following assumptions:

c. ***Booking priority:*** Consistent with industry practice, non-disrupted passengers have priority over disrupted passengers. Therefore, non-disrupted passengers are not reassigned to an itinerary different from their scheduled itinerary.
d. ***No bumped passengers:*** We assume all non-disrupted passengers fly their booked itineraries, with passenger bumping not allowed.
e. ***Rebooking order:*** Disrupted passengers are re-accommodated under a First-Disrupted-First-Recovered (FDFR) policy. When a flight is canceled, the order in which disrupted passengers are re-accommodated depends on the disrupted passengers' check-in times. Because we do not know this information, we rank the disrupted passengers randomly in our disruption queue.
f. ***Time passengers are informed about flight schedule disruptions:*** We do not have information pertaining to the time at which passengers are informed that their schedules are disrupted. We have, therefore, assumed that passengers disrupted by a canceled flight are notified when the flight is scheduled to depart.

g. ***Passengers re-accommodated on the next-day's flights or on other airlines' flights:*** In PDC, there are two situations where disrupted passengers are recovered by other airlines:

- *Situation 1:* For some disrupted passengers, if the airline has *only one* fight per day for certain routes (between the disrupted airports and their final destination), these groups are assumed to be recovered either the next day or by other airlines on the same day. If these passengers are disrupted before 6pm, we assume they are recovered by other airlines; otherwise, they must wait to be re-accommodated on the next day's flight.
- *Situation 2:* If a passenger delay exceeds the predefined *Maximum Passenger Delay (MPD)* threshold (of 15 hours, see Bratu, 2003, for analysis supporting this selection), then he/she is re-accommodated on a different airline. In effect, this limit serves as a crude model of inter-airline passenger re-accommodation. To be more accurate in estimating the resulting delay to these passengers, information regarding seat availabilities on other airlines and airline policies are required.

h. ***Passenger Minimum Connection Time:*** Passengers require at least the *MCT* to transfer to their outgoing flights. Although *MCT* varies for each connecting passenger at each airport because of differences in the distances between gates and disembarking times, we set *MCT* to 15 minutes.

i. ***No Luggage Disruption:*** Although checked-in luggage is another important dimension of passenger service, we do not consider luggage disruption in our analysis.

PDC Algorithm. Inputs to the PDC include: (1) flight schedules with given aircraft routings; (2) itineraries generated by the IGA; (3) for each scheduled itinerary, the number of booked passengers (that is, the outputs from the PAP); and (4) the planned and actual flight departure time, arrival time, departure delay and arrival delay for each flight in the schedule as well as each canceled and diverted flight (from ASQP). The steps of the PDC algorithm are illustrated in Figure 4-2. In STEP 1, for all flights in the schedule, we determine which itinerary is disrupted. The recovery queue is built in STEP 2, according to our specified recovery policy. In STEP 3, each disrupted passenger is re-accommodated on a feasible itinerary that arrives as early as possible at the desired destination or on a different airline (sees ***Assumption g***). In STEP 4, disrupted passengers, for whom there is no efficient recovery itinerary within a specified time frame, are assumed to be recovered on different airlines. In STEP 5, passenger delay estimations are aggregated and passenger schedule reliability statistics are computed.

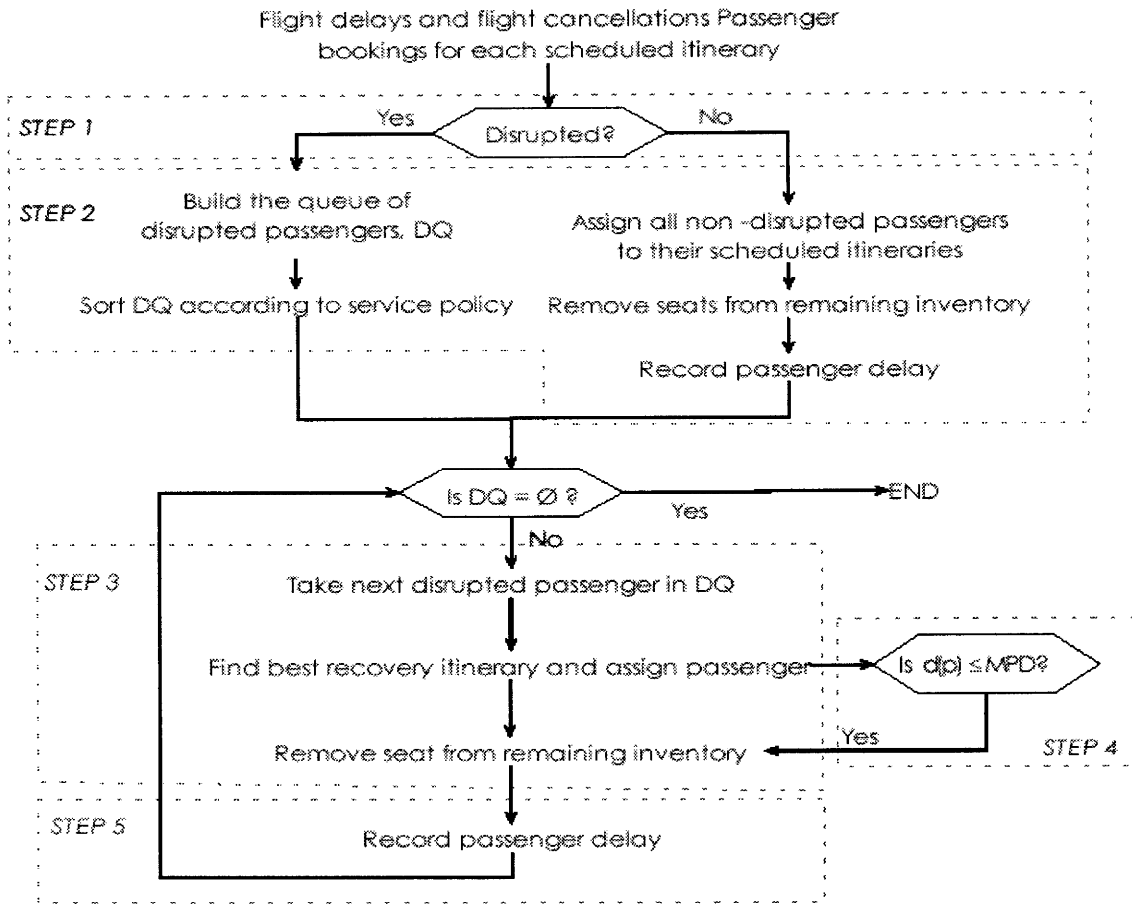


Figure 4-2: Passenger Delay Calculator schematic

Details of the steps of PDC are as follows:

□ **STEP 1:** Identifying disrupted and non-disrupted itineraries.

If a passenger schedule is disrupted, the airline will search for a *recovery itinerary* to re-accommodate the disrupted passenger. A recovery itinerary is defined as a sequence of flights with at least one seat available on each flight to re-accommodate a disrupted passenger to his/her desired destination. For each passenger p on an itinerary containing, for example, flights $f(1)$ followed by $f(2)$, Figure 4-3 illustrates the sequential algorithm that determines if passengers are disrupted:

❖ Is f(1) cancelled?

⇨ If yes, passenger p is disrupted, $p \in D$ and disruption time $DT(p) = PDT(f(1))$

❖ Else is f(2) cancelled?

⇨ If yes, passenger p is disrupted, $p \in D$ and disruption time $DT(p) = PDT(f(2))$

❖ Else, is $ADT(f(2)) - AAT(f(1)) < MCT$?

⇨ If yes, passenger p is disrupted, $p \in D$ and disruption time $DT(p) = ADT(f(2))$

❖ Otherwise, passenger p is not disrupted, $p \in ND$, and arrival time is $AAT(f(2))$, and $d(p) = Max(0; AAT(f(2)) - PAT(f(2)))$.

Figure 4-3: Passenger disruption checking algorithm

Given the partitioning of passengers into the disrupted passenger subset D and the non-disrupted passenger subset ND, the algorithm reserves seats first for each non-disrupted passenger, as it is industry practice to give them priority over disrupted passengers (as discussed in the service priority assumptions). Then, delay statistics for non-disrupted passengers are recorded and available seat inventories are decremented to reflect their assignments.

□ **STEP 2:** Ordering the disrupted passengers.

The second step of PDC is to build the queue of disrupted passengers. Various service policies are possible, including: (1) re-accommodating passengers in the order in which they are disrupted, called First-Disrupted-First-Recovered (FDFR); (2) re-accommodating passengers in the order of decreasing fare class value; or (3) re-accommodating passengers in the order of decreasing frequent flyer status. In this analysis, we sort the disrupted passengers in D according to the first policy because detailed information on fare class value and frequent flyer status are not available.

When two different passengers are disrupted at the same time, we randomly select whom to re-accommodate first.

□ **STEP 3:** Re-accommodating disrupted passengers.

For each passenger, the PDC algorithm finds the recovery itinerary commencing at the airport where the passenger is located and arriving the earliest to the passenger's desired destination. Two lists of recovery itineraries for disrupted passenger *p* are generated: the *Direct Itinerary List* (*DIL(p)*) for which itineraries have one flight leg only, and the C*onnecting Itinerary List*, *CIL(p,H)*, for which itineraries have multiple flight legs and connect through hub airport *H*. Once *DIL(p)* and *CIL(p,H)* are constructed for each hub airport, the combined list is sorted according to arrival time and passenger *p* is re-assigned to the earliest arriving itinerary with seat availability. For details of the recovery itinerary search algorithm, refer to Bratu and Barnhart (2005) [3].

□ **STEP 4:** Generating outputs.

The output of the PDC algorithm is a vector of passenger delay statistics, including average delays for each passenger, and numbers of passengers in different groups, such as local, connecting, disrupted, non-disrupted, disrupted and recovered on the same day, and disrupted and stranded overnight.

Chapter 5

Passenger Delay Analysis

5.1 Introduction

In this chapter, we compare passenger delay statistics between the legacy network carrier and the low-cost carrier on the two different days. As mentioned in Chapter 3, passenger delays arise from flight delays and cancellations. Additionally, other factors such as network structures, passenger mix, load factors, and flight schedule design, also have a significant impact on passenger on-time performance. This chapter aims to establish relationships between passenger delays and flight leg delays, cancellation rates, load factors, network structures, passenger mix, and schedule design. In the next section, we compare the network structures and passenger mixes of Airline A and Airline B. We also discuss how flight schedules differ between the two airlines and present a load factor analysis. We then show the differences in passenger delay and disruption activities of the two airlines. Explanations of these differences are provided.

5.2 Network Structure and Passenger Mix

Airline A operates a "hub-and-spoke" network, while Airline B operates more of a "point-to-point" network, although many connecting opportunities are provided at "hub" networks. In this section, we compare the network operations and passenger mix (local and connecting) of Airline A and Airline B. We first identify the three largest airports (in terms of total enplaned passengers) at which each airline operates (Figure 5-1) using data provided by BTS [4]. Then, for each major airport of the two airlines, we compute the number of aircraft operations and connecting passengers in each one-hour time window. Along the "time-window" axis, "1" represents 4:00am – 4:59am, "2" represents 5:00am – 5:59am, and so on. The last label "20" represents 11:00pm – 11:59pm. Between 0:00am and 3:59am, neither Airline A nor Airline B operates domestic flights.

The analysis of passenger mix (local vs. connecting) by airport (Figure 5-2 to Figure 5-7) provides us useful insights into the airlines' passenger operations. For Airline A and Airline B, the percentages of connecting passengers at their respective major airports are comparable. Like Airline A, Airline B also exhibits a "hub" operation at its three largest "hubs" (indicated by the high percentages of connecting passengers). However, there is a difference in the level of connecting passenger traffic between the major airports of Airline A and Airline B. In particular, the major hubs of Airline A accommodate a larger share of A's connecting passenger traffic compared to the share of B's connecting passengers captured at the major airports of Airline B. In other words, connecting passengers are distributed more evenly in Airline B's system and hence, the shares of connecting passengers in Airline B's major airports are not as significant as Airline A's. In Figure 5-8 to Figure 5-10, we show airports with fewer operations and smaller percentages of connecting passengers compared to the three largest "hubs" in Airline B's operation. This suggests that in B's system, some airports act like "connecting hubs" with higher percentages of connecting passenger traffic than at other airports in B's network; airports which accommodate more local passengers. Strictly speaking, "point-to-point" service is an inaccurate description of our low-cost carrier's network operations. Rather, Airline B uses "hubs" to serve various levels of connecting passenger traffic in the network. Further evidence to support this finding is that our estimates show that an overall connecting share for the legacy carrier (the low-cost carrier) of 35% (48%), and a local passenger share of 65% (52%).

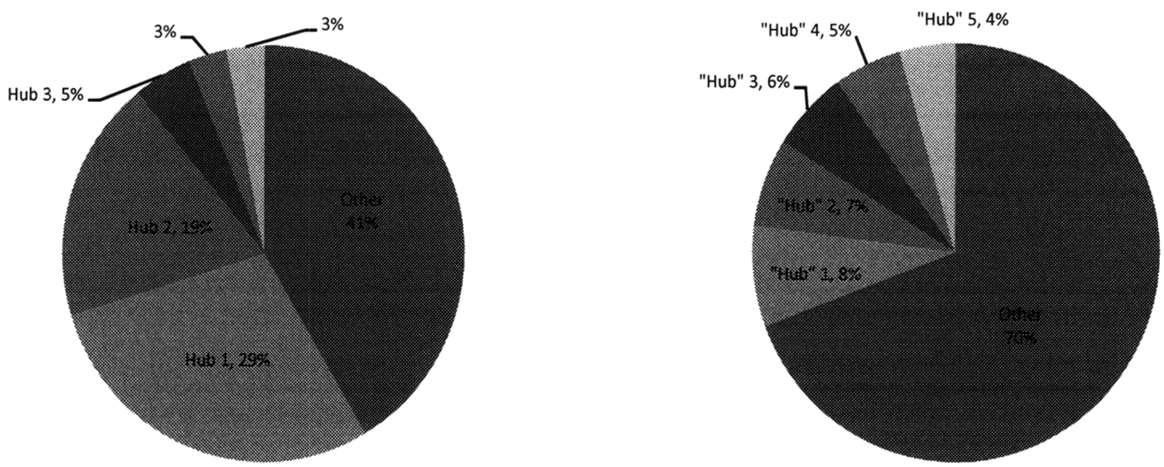
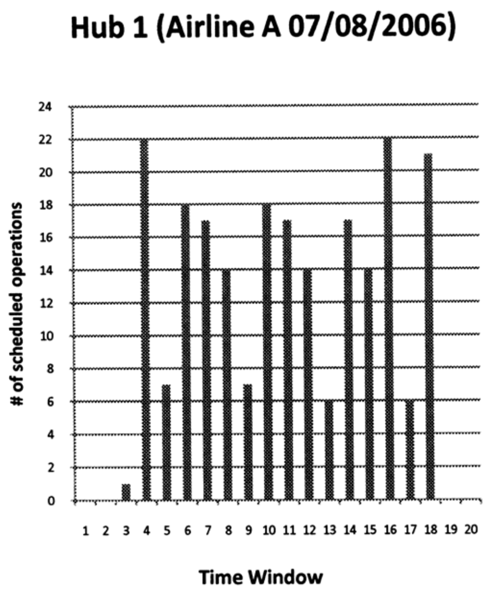


Figure 5-1: Market share in Airline A's (left) and Airline B's (right) total enplaned passengers[12]

[12] Enplaned passengers: the total number of revenue passengers boarding aircraft



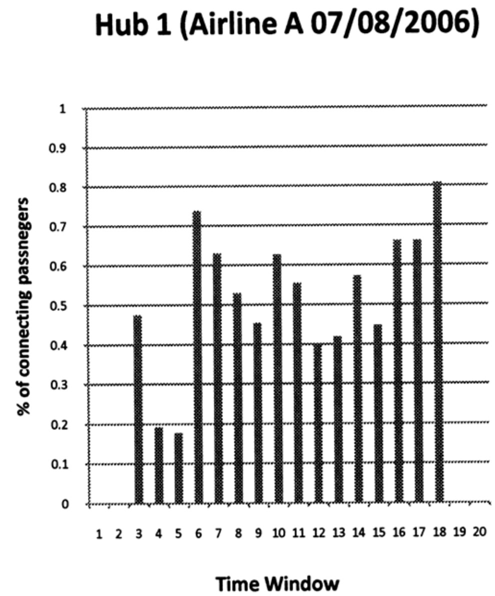
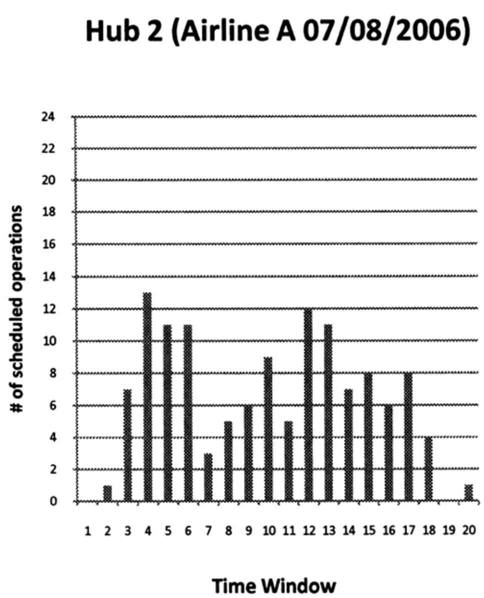


Figure 5-2: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 1



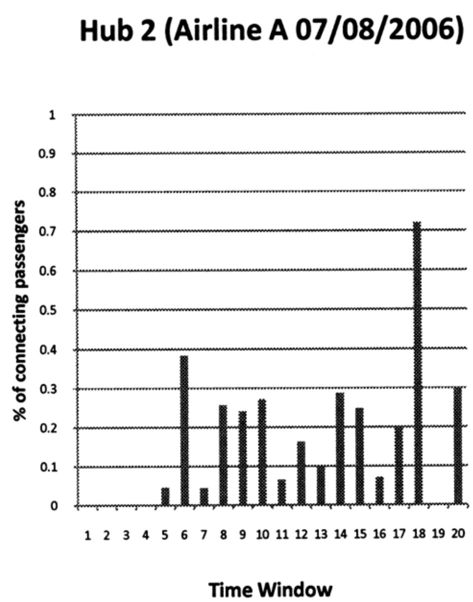


Figure 5-3: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 2

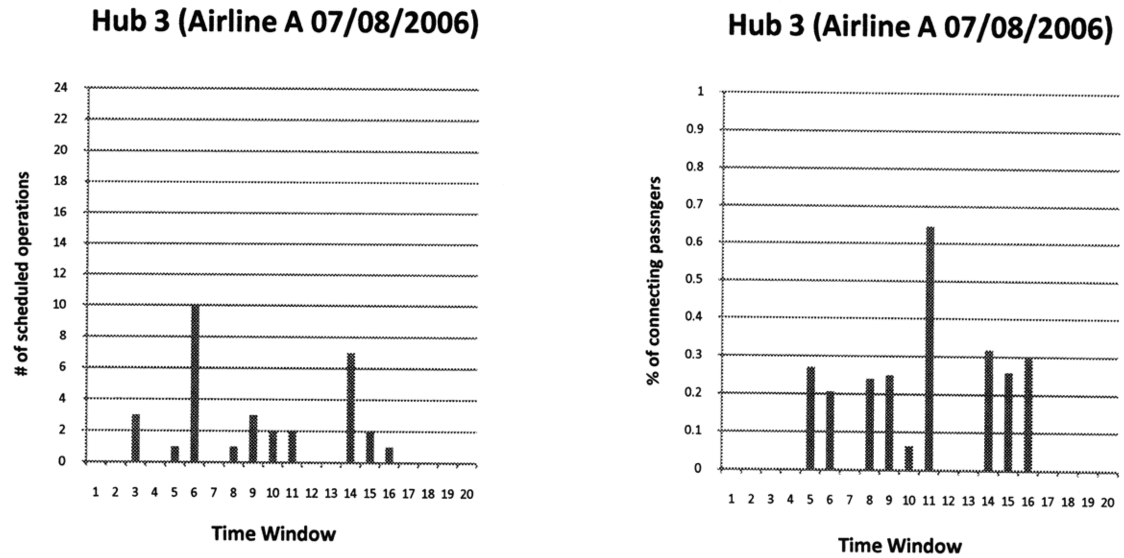


Figure 5-4: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Hub 3

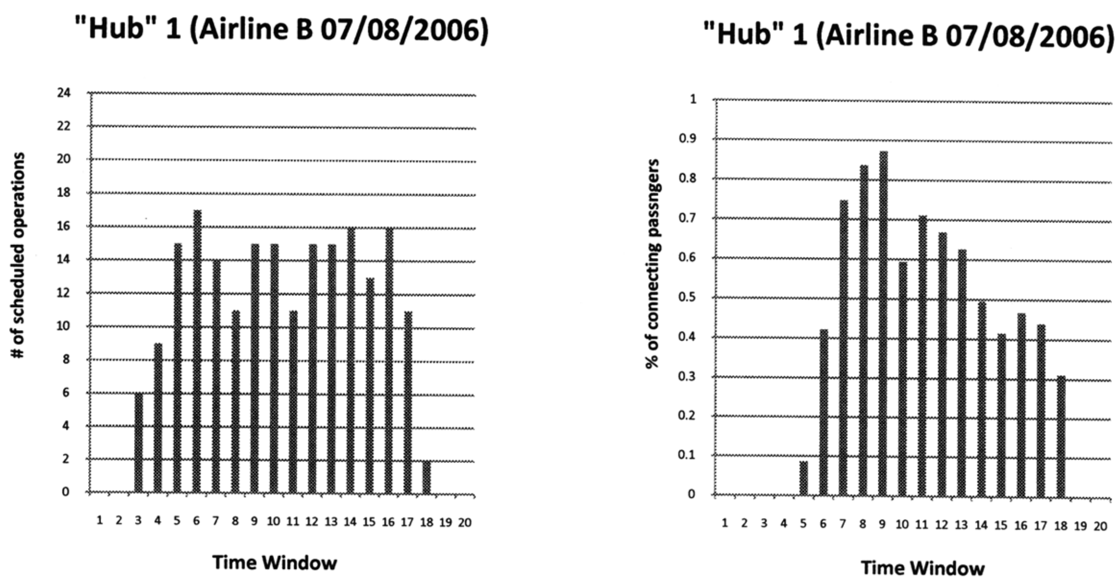


Figure 5-5: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 1

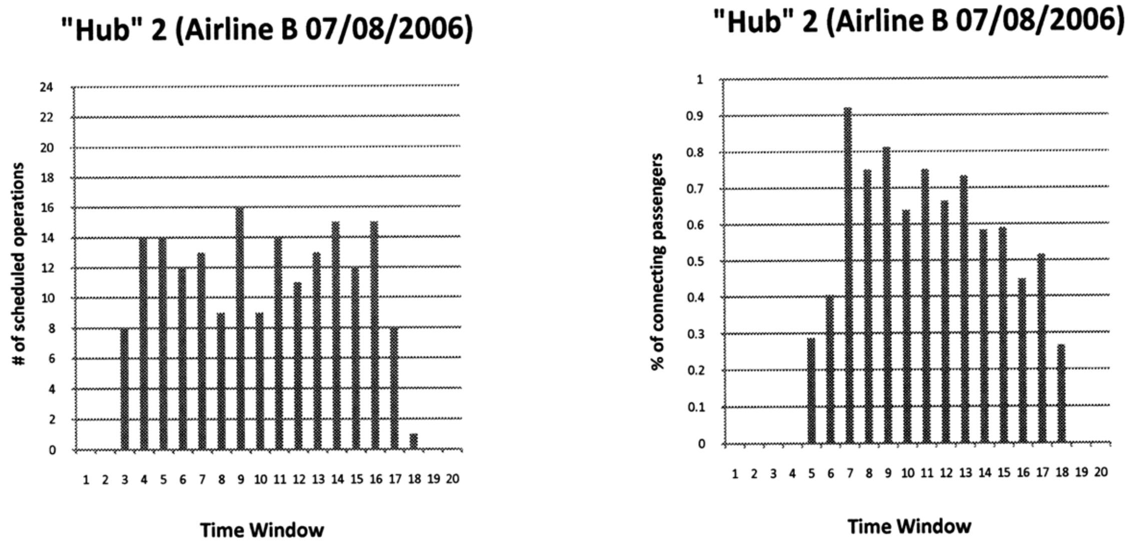


Figure 5-6: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 2

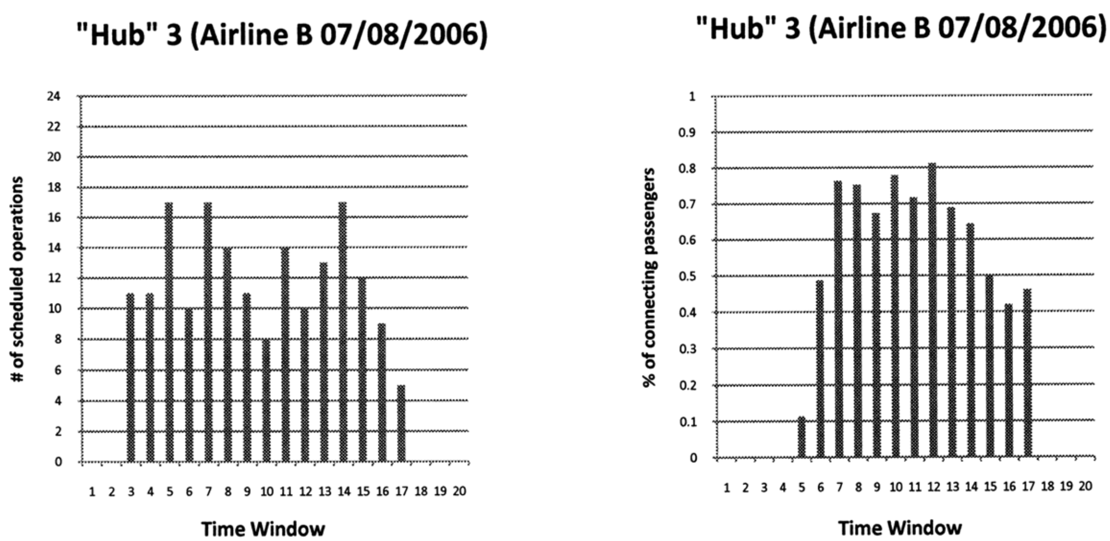
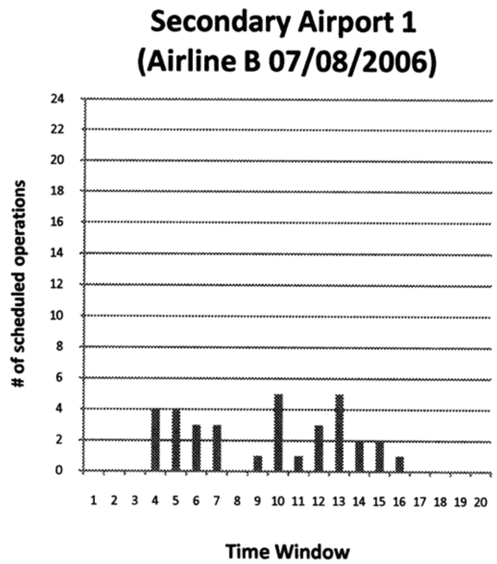


Figure 5-7: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at "Hub" 3



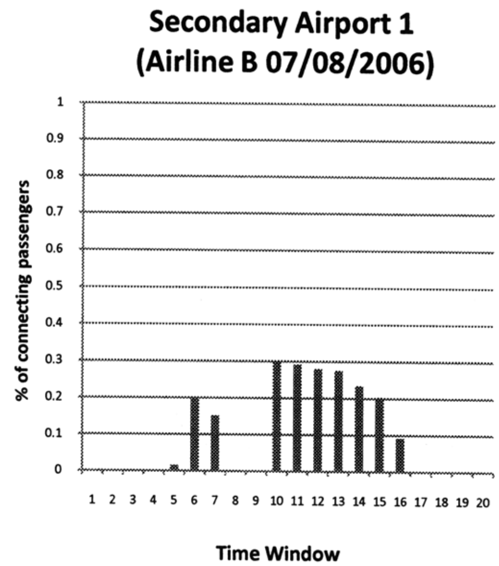
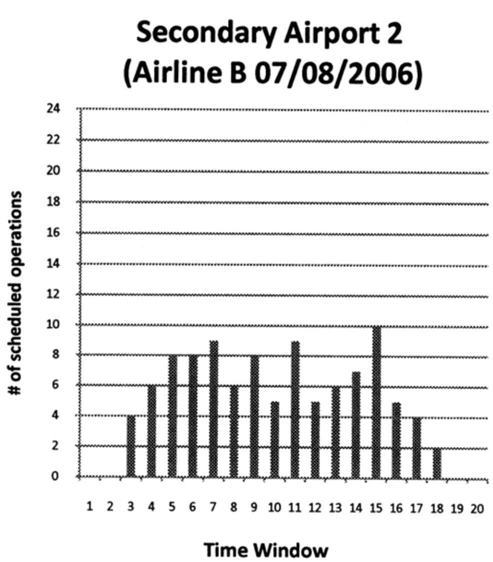


Figure 5-8: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 1



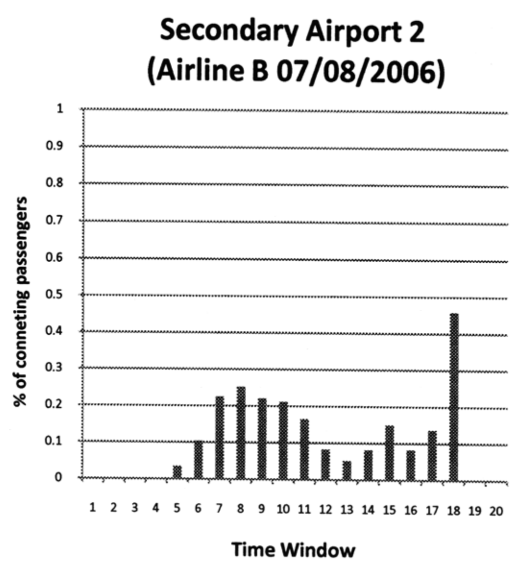
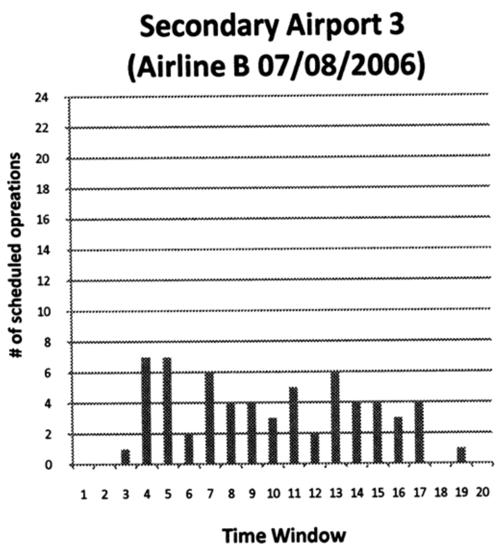


Figure 5-9: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 2



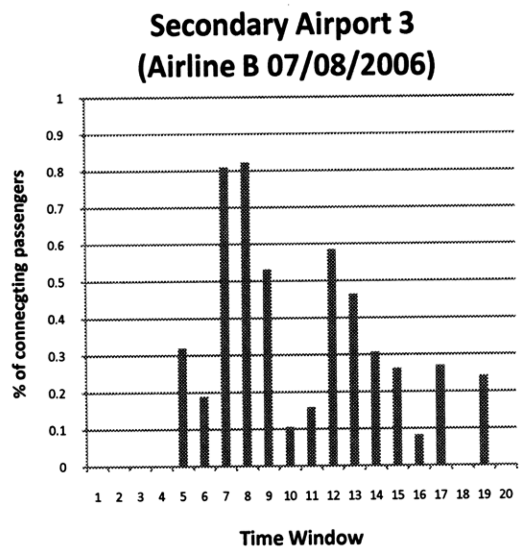


Figure 5-10: Scheduled flight operations (left) and percentage of connecting passengers (right) in each one-hour time window at Secondary Airport 3

Peaked Schedules vs. De-peaked Schedules

Figure 5-2 (left) and Figure 5-4 (left) depict the number of flight operations for each one-hour window at two major hubs of Airline A. As illustrated by the figures, these two schedules create departure peaks at the hub with each peak planned to last about one to two hours. Airline A operates one de-peaked hub (Figure 5-3), while, as shown in Figures 5-5, 5-6, and 5-7, Airline B has de-peaked schedules at its three largest "hubs".

In a de-peaked schedule, aircraft need not wait on the ground for connecting passengers and therefore ground turn times are reduced, leading to increased aircraft utilization. This is evidenced by Table 5-1, which displays the daily utilization per aircraft of Airline A and Airline B from 2005 to 2007, respectively. For both block hours and airborne hours, Airline B achieved a higher utilization per aircraft than did Airline A.

Note that the numbers of departures performed by Airline B are almost twice as many as those performed by Airline A, indicating (with the airborne hours information) that Airline B flies shorter flights on average.

Daily utilization per aircraft (Airline A)	2005	2006	2007
Block hours	9.08	9.57	10.07
Airborne hours	7.46	7.8	8.2
Departures	3.3	3.47	3.65

Daily utilization per aircraft (Airline B)	2005	2006	2007
Block hours	11.13	11.22	11.19
Airborne hours	9.58	9.68	9.59
Departures	6.53	6.49	6.37

Table 5-1: Daily utilization per aircraft for Airline A (top) and Airline B (bottom)

Source: MIT Airline Data Project

De-peaked schedules are more robust in the sense that airport capacity reductions resulting from weather can have less of an impact than in the case of peaked operations with their high-levels of peak demand for capacity.

5.3 Load Factors

Using information from T-100 Segment data (BTS (2006) [10]), we compute average load factors per flight leg of the two airlines in July, 2006. Airline A had an average load factor of 83.43% per flight leg and Airline B had 77.23%. Using the PAP method developed in Chapter 4, we estimate the average load factor to be 79.20% (78.00%) for Airline A and 81.20% (74.30%) for Airline B on the two days under consideration. With our PAP, we find that Airline B transported 4.4 times more passengers on its domestic flights than Airline A on non-week days like July 8 and 3.2 times more passengers on week days like July 12. The numbers of passengers we estimate are 60.2k (86.4k) for Airline A and 262.8k (278.0k) for Airline B on July 8 (July 12). In Figure 5-11, we plot the percent of flight legs with load factors greater than or equal to selected values, for both airlines in July 2006. The vertical gap between the two curves represents the difference in the percentage of flight legs with load factors greater than or equal to a fixed value. According to these plots, we find:

- 58.58% of Airline A's flights had a load factor greater than or equal to 85% compared to only 33.72% for Airline B;
- 40.05% of Airline A's flights had a load factor greater than or equal to 90% compared to only 21.14% for Airline B;
- 15.71% of Airline A's flights had a load factor greater than or equal to 95% compared to only 7.34% for Airline B;
- 2.39% of Airline A's flights had all seats sold out compared to only 1.60% for Airline B.

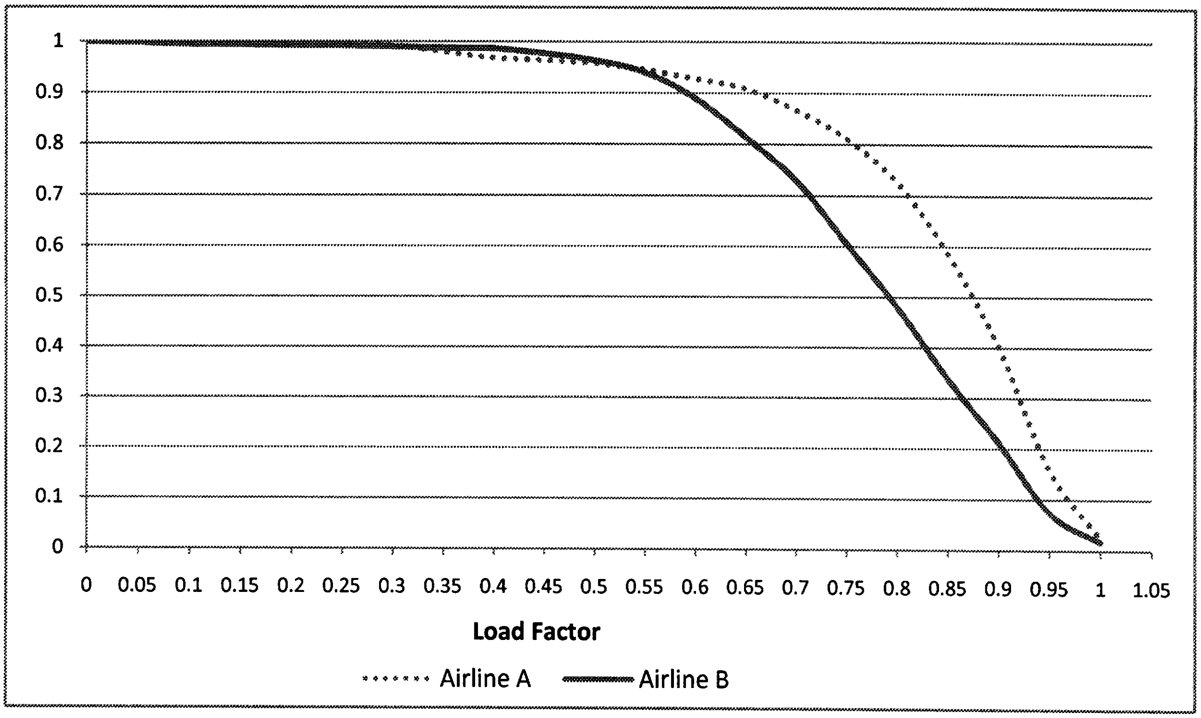


Figure 5-11: Percent of flight legs with load factor greater than or equal to various levels in July, 2006

5.4 Passenger Delay Statistics

As in Chapter 3, our analysis applies only to jet-operated flight legs because the ASQP data set includes only jet operated flight leg information. Using the 3-stage approach described in Chapter 4, we compute the passenger delay statistics for the two airlines on July 8 and July 12, 2006 (shown in Table 5-2). Flight delay statistics from Chapter 3 are retained in Table 5-2 to assist our understanding of differences in the airlines' passenger delays. In Table 5-3 (Table 5-4), we display the differences (ratios) between statistics of the two airlines and between statistics of the two days for the same airline.

	Airline A (07/08/2006)	Airline B (07/08/2006)	Airline A (07/12/2006)	Airline B (07/12/2006)
1. Number of flight operations (domestic U.S.)	727	2698	922	3116
2. Number of onboard passengers (domestic U.S., in thousands)	60.2	262.8	86.4	278.0
3. Average load factor per flight leg	79.20%	81.20%	78.00%	74.30%
Average Flight Delay (F-Delay)				
4. 15 minutes on time performance (*15-OTP*)	87.60%	89.00%	60.60%	75.80%
5. Percentage of delayed flights* (only flights operated)	12.40%	11.00%	39.40%	24.20%
6. Percentage of cancelled flights	0	0.44%	1.52%	0.89%
7. Average delay of operated flights (minutes)	6.36	4.82	38.75	12.28
8. Average delay of flights with positive delays (minutes)	19.36	17.5	67.16	25.74
Average Passenger Delay (P-Delay)				
9. Average delay of all passengers (minutes)	8.11	8.74	53.84	21.28
10. Percentage of delayed passengers*	13.63%	14.79%	43.49%	36.77%
11. Percentage of *disrupted* passengers	0.40%	0.44%	2.80%	1.25%
12. Average delay of *non-disrupted* passengers (minutes)	7.31	5.03	41.48	14.23
13. Maximum delay of *non-disrupted* passengers (minutes)	185	105	457	230
14. Average delay of *disrupted* passengers (minutes)	261.76	409.39	482.99	578.25
15. Average delay of passengers with positive delays (minutes)	25.78	26.47	84.97	44.07
Ratio of P-Delay to F-Delay				
9 to 7	1.28	1.81	1.38	1.73
12 to 7	1.15	1.04	1.07	1.16
14 to 7	41.16	84.94	12.46	47.09
Difference of P-Delay and F-Delay				
9 to 7	1.75	3.92	15.09	9
12 to 7	0.95	0.21	2.73	1.95
14 to 7	255.4	404.57	444.24	565.97

* Delayed flights (delayed passengers) are the flights (passengers) with delays greater than 15 minutes

Table 5-2: Passenger and flight delay statistics

	A8-B8*	A12-B12**	A12-A8***	B12-B8****
1. Number of flight operations (domestic U.S.)	**-1971**	**-2194**	**195**	**418**
2. Number of onboard passengers (domestic U.S., in thousands)	**-202.6**	**-191.6**	**195**	**15.2**
3. Average load factor per flight leg	**-2.00%**	**3.70%**	**-1.20%**	**-6.90%**
Average Flight Delay (F-Delay)				
4. 15 minutes on time performance (*15-OTP*)	**-1.40%**	**-15.20%**	**-27.00%**	**-13.20%**
5. Percentage of delayed flights (only flights operated)	**1.4%**	**15.2%**	**27%**	**13%**
6. Percentage of cancelled flights	**0**	**0.01**	**0.02**	**0**
7. Average delay of operated flights (minutes)	**1.54**	**26.47**	**32.39**	**7.46**
8. Average delay of flights with delays (minutes)	**1.86**	**41.42**	**47.8**	**8.24**
Average Passenger Delay (P-Delay)				
9. Average delay of all passengers (minutes)	**-0.63**	**32.56**	**45.73**	**12.54**
10. Percentage of delayed passengers	**-1.16%**	**6.72%**	**29.86%**	**21.98%**
11. Percentage of *disrupted* passengers	**-0.04%**	**1.55%**	**2.40%**	**0.81%**
12. Average delay of *non-disrupted* passengers (minutes)	**2.28**	**27.25**	**34.17**	**9.2**
13. Maximum delay of *non-disrupted* passengers (minutes)	**80**	**227**	**272**	**125**
14. Average delay of *disrupted* passengers (minutes)	**-147.63**	**-95.26**	**221.23**	**168.86**
15. Average delay of delayed passengers (minutes)	**-0.69**	**40.9**	**59.19**	**17.6**
Ratio of P-Delay to F-Delay				
9 to 7	**-0.53**	**-0.35**	**0.1**	**-0.08**
12 to 7	**0.11**	**-0.09**	**-0.08**	**0.12**
14 to 7	**-43.78**	**-34.83**	**-28.7**	**-37.85**

*A8-B8: The differences between statistics of Airline A on July 8 and statistics of Airline B on July 8
**A12-B12: The differences between statistics of Airline A on July 12 and statistics of Airline B on July 12
***A12-A8: The differences between statistics of Airline A on July 12 and statistics of Airline A on July 8
****B12-B8: The differences between statistics of Airline B on July 12 and statistics of Airline B on July 8

Table 5-3: Absolute differences in passenger and flight delay statistics

	A8/B8*	A12/B12**	A12/A8***	B12/B8****
1. Number of flight operations (domestic U.S.)	0.27	0.3	1.27	1.15
2. Number of onboard passengers (domestic U.S., in thousands)	0.23	0.31	1.44	1.06
3. Average load factor per flight leg	0.98	1.05	0.98	0.92
Average Flight Delay (F-Delay)				
4. 15 minutes on time performance (*15-OTP*)	0.98	0.8	0.69	0.85
5. Percentage of delayed flights (only flights operated)	1.13	1.63	3.18	2.18
6. Percentage of cancelled flights	0	1.71	NA	2.02
7. Average delay of operated flights (minutes)	1.32	3.16	6.09	2.55
8. Average delay of flights with delays (minutes)	1.11	2.61	3.47	1.47
Average Passenger Delay (P-Delay)				
9. Average delay of all passengers (minutes)	0.93	2.53	6.64	2.43
10. Percentage of delayed passengers	0.92	1.18	3.19	2.49
11. Percentage of *disrupted* passengers	0.91	2.24	7	2.84
12. Average delay of *non-disrupted* passengers (minutes)	1.45	2.91	5.67	2.83
13. Maximum delay of *non-disrupted* passengers (minutes)	1.76	1.99	2.47	2.19
14. Average delay of *disrupted* passengers (minutes)	0.64	0.84	1.85	1.41
15. Average delay of delayed passengers (minutes)	0.97	1.93	3.3	1.66
Ratio of P-Delay to F-Delay				
9 to 7	0.71	0.80	1.08	0.96
12 to 7	1.11	0.92	0.93	1.12
14 to 7	0.48	0.26	0.30	0.55

*A8/B8: The ratios of statistics of Airline A on July 8 to statistics of Airline B on July 8

**A12/B12: The ratios of statistics of Airline A on July 12 to statistics of Airline B on July 12

***A12/A8: The ratios of statistics of Airline A on July 12 to statistics of Airline A on July 8

****B12/B8: The ratios of statistics of Airline B on July 12 to statistics of Airline B on July 8

Table 5-4: Ratios in passenger and flight delay statistics

From the tables above, several observations are made for July 8, 2006 in terms of passenger delays and disruptions:

1. The maximum delay of non-disrupted passengers for Airline A was 1.76 times greater than that for Airline B.
2. Airline B's non-disrupted passengers experienced less delay than Airline A's. Notice that Airline A's operated flights experienced an average delay of 6.36 minutes while Airline B's operated flights experienced an average of 4.82 minutes. Additionally, the percentage of Airline A's delayed flights (12.40%) was higher than that of Airline B's delayed fights (11.0%). These differences resulted in a higher average delay for Airline A's non-disrupted passengers.
3. The overall percentages of disrupted passengers were comparable for both airlines with Airline B having a slightly higher percentage.
4. All passenger disruptions of Airline A were due to missed connections because there were no flight cancellations. On the other hand, passenger disruptions of Airline B arose from a mix of cancelled flights and missed connections.
5. Airline B had a higher load factor than Airline A.
6. Airline B's disrupted passengers experienced 1.56 times more average delay than Airline A's disrupted passengers. The fact that Airline A had no flight cancellations and lower average load factors explains in part why Airline B's disrupted passengers had a higher average delay than Airline A's. When a disruption is caused by a flight cancellation rather than a missed connection, the cancellation causes all passengers on the flight to compete for seats. In contrast, a delayed rather than cancelled flight results in fewer missed connections to a given flight, which makes the recovery process easier. Additionally, the frequency of markets served by each airline also affects its disrupted passenger delay in the sense that higher market frequency translates into a quicker recovery when disruptions occur.

7. Overall, the average delay of all passengers (disrupted and non-disrupted) and the average delay of passengers with positive delays were slightly higher for Airline B than for Airline A.
8. The percentage of delayed passengers was slightly higher for Airline B than for Airline A.
9. The ratio of overall passenger delay to operated flight delay was higher for Airline B than for Airline A.
10. The ratios of non-disrupted passenger delay to operated flight delay were comparable for both airlines.
11. The ratio of disrupted passenger delay to operated flight delay for Airline B was twice as much as that for Airline A.

For July 12, 2006, the following observations are made from the tables above, regarding passenger delays and disruptions:

1. On average, Airline A had a higher load factor (78.00%) than Airline B (74.30%) per flight leg.
2. Airline A had 1.71 times more cancellations than Airline B. In contrast to July 8, 2006, Airline B's cancellations doubled and Airline A's cancellations increased from none to a significant number (1.52% of flights were cancelled).
3. The maximum delay of non-disrupted passengers for Airline A was twice as much as that for Airline B.
4. The average delay of non-disrupted passengers for Airline A was three times as much as that for Airline B. Notice that the average delay of Airline A's operated flights was 3.16 times higher than that of Airline B's operated flights. Additionally, the percentage of Airline A's delayed flights (39.40%) was higher than that of Airline B's delayed flights (24.20%). For flights with positive delays, the average delay for Airline A was 2.61 times higher than that for Airline B.

These differences resulted in a higher average delay for Airline A's non-disrupted passengers.

5. In contrast to July 8, 2006, the overall percentage of disrupted passengers was increased by a factor of 7 for Airline A and a factor of 2.84 for Airline B.
6. The overall percentage of disrupted passengers for Airline A was 2.24 times more than that for Airline B.
7. Airline B's disrupted passengers experienced 1.20 times more delay on average than Airline A's.
8. Overall, the average delay of all passengers (disrupted and non-disrupted) for Airline A was 2.5 times higher than for Airline B.
9. The average delay of passengers with positive delays was 1.93 times higher for Airline A than for Airline B. The percentage of delayed passengers was also higher for Airline A than for Airline B.
10. The ratio of overall passenger delay (and non-disrupted passenger delay) to operated flight delay was higher for Airline B than for Airline A.
11. The ratio of disrupted passenger delay to operated flight delay for Airline B was almost four times as much as that for Airline A.

Compared to July 8, 2006 (the "low-delay" day), passenger on-time performances were worse for both airlines on July 12, 2006 (the "high-delay" day). This is also true in terms of both airlines' flight on-time performance. In particular, compared to July 8, 2006, the average delay of operated flights was increased by a factor of 6.09 for Airline A and a factor of 2.55 for Airline B. The average delay of flights with positive delays was increased by a factor of 3.47 for Airline A and a factor of 1.47 for Airline B. Also, the percentage of delayed flights was increased by a factor of 3.18 for Airline A and 2.18 for Airline B. In particular, we observe:

1. The percentage of delayed passengers was increased by a factor of 3.19 for Airline A and 2.49 for Airline B.
2. The overall percentage of disrupted passengers was increased by a factor of 7 for Airline A and a factor of 2.84 for Airline B on July 12, 2006.
3. The maximum delay of non-disrupted passengers was increased by a factor of 2.47 for Airline A and a factor of 2.19 for Airline B.
4. The average delay of all passengers was increased by a factor of 6.64 for Airline A and a factor of 2.43 for Airline B.
5. The average delay of passengers with positive delays was increased by a factor of 3.30 for Airline A and a factor of 1.66 for Airline B.

Summary of the Delay Statistics

For each airline, the average delay of its operated flights and the average delay of its *non-disrupted* passengers were comparable on the two days. However, the discrepancies between delay of operated flights and average delay of *all* passengers were increased for both airlines on the "high-delay" day. This is because the overall percentages of disrupted passengers were increased significantly for both airlines on July 12, 2006. This result confirms findings from previous studies (Bratu and Barnhart (2005) [3], Wang et al. (2007) [25]) that simple flight-based statistics tend to underestimate passenger delays on a "high disruption" day because disrupted passengers experience longer delays on average than do flights.

Highlight Finding 1 – Differences in Aircraft and Passenger Delay between Airline A and Airline B on the "High-Delay" Day

One of the key observations from Table 5-2 is that although both airlines had "high-delay" in flight operations on July 12, Airline A suffered almost three times as much aircraft delay and 2.5 times as much passenger delay in absolute minutes as Airline B.

In Chapter 3.2.2, we find that on July 12, 2006, Airline A had 13% of flights experiencing delay propagation and Airline B had 18.7%. However, Airline A suffers twice as much propagated delay (12.48 minutes) on average as Airline B (6.19 minutes). Airline B, then, had a higher percentage of flights with propagated delay than Airline A but experienced much less passenger delay. We believe the fact that Airline B had a higher percentage of flights with propagated delay (than Airline A did) lies in an important difference between Airline A and Airline B in how they build their schedules; i.e., Airline B plans less turn time slack (than Airline A does). Additionally, Airline B can afford to schedule its turn time with less slack and on "high-delay" days let delay propagate with fewer passengers being disrupted because Airline B plans longer connection times for its passengers than Airline A does. Our analysis shows that the average passenger connecting time for Airline A's passengers was 97.87 (99.41) minutes compared to 134.65 (135.29) minutes for Airline B on July 8 (July 12), 2006.

Highlight Finding 2 – Discrepancy between Various Delay Measures

One interesting finding is that on both days, the ratios of passenger delay to operated flight delay for Airline B were higher than the corresponding values for Airline A. This difference is most obvious in terms of the ratio of disrupted passenger delay to operated flight delay, although on the "high-delay" day, the percentage of disrupted passengers was much higher for Airline A than for Airline B. In particular, the following observations are made:

- On July 8 (July 12), the ratio of overall passenger delay to operated flight delay was 1.81 (1.73) for Airline B and 1.28 (1.38) for Airline A.
- On July 8 (July 12), the ratio of disrupted passenger delay to operated flight delay was 84.94 (47.09) for Airline B and 41.16 (12.46) for Airline A.

Further, the discrepancy between average delay of disrupted passengers and non-disrupted passengers was also much higher for Airline B than for Airline A:

- On July 8 (July 12), 2006, for Airline A, the disrupted passengers experienced 35.8 (11.6) times more average delay than the non-disrupted passengers. For Airline B, the disrupted passengers experienced 81.4 (40.6) times more average delay than the non-disrupted passengers.

These observations indicate that the relationship between flight delay and passenger delay might be carrier-specific. In particular, we believe the cause of the above differences is the longer average time for Airline B's disrupted passengers as they wait for the next available itinerary to their destinations, relative to that of Airline A's disrupted passengers. We define scheduled waiting time until the next available itinerary with seat availability and commencing at the airport where the disrupted passenger is located and arriving the earliest to the passenger's desired destination as the difference between the disruption time of the passenger and the scheduled departure time of that itinerary. Similarly, we define actual waiting time until that itinerary as the difference between the disruption time of the passenger and the actual departure time of that itinerary. Scheduled waiting time and actual waiting time reported in Table 5-5 are averaged over all disrupted passengers on that day. We discover the following:

1. Table 5-5 shows that compared to Airline A, Airline B had greater average scheduled waiting time and average actual waiting time, on July 8 and July 12, respectively[13].
2. Table 5-6 shows that the average number of recovery alternatives for each Airline A disrupted passenger is 1.3 times as much as that for each Airline B disrupted

[13] The calculation of average waiting time only considers alternative itineraries within the same airlines and excludes waiting time for the availability of alternative itineraries from other airlines.

passenger on July 8, and 1.2 times on July 12. The average scheduled and actual waiting time for each Airline B disrupted passenger is 2.92 (2.66) times as much as that for each Airline A disrupted passenger on July 8 and 1.59 (1.15) times as much on July 12.

	Airline A (07/08/2006)	**Airline A (07/12/2006)**	**Airline B (07/08/2006)**	**Airline B (07/12/2006)**
Scheduled waiting (in minutes)	98.81	164.36	288.33	261.59
Actual waiting (in minutes)	110.38	238.28	293.17	274.80

Table 5-5: The average waiting time (scheduled and actual) per passenger until the next available itinerary

	Number of recovery alternatives (A to B)	**Scheduled waiting (B to A)**	**Actual waiting (B to A)**
07/08/2006	1.3	2.92	2.66
07/12/2006	1.2	1.59	1.15

Table 5-6: The ratios per passenger of the number of recovery alternatives, scheduled waiting time, and actual waiting time of Airline A to those of Airline B, respectively

A further comparison of the degree to which passengers are disrupted is shown in Table 5-7. Chapter 4.4.3 discusses the situations where disrupted passengers are assumed to be re-accommodated on the airline's own flights on the same day, on the next-day's flights, or on other airlines' flights. We observe that, on both July 8 and July 12, Airline B had a lower percentage of disrupted passengers recovered within its own system on the same day than did Airline A. As a result, disrupted passengers of Airline A experienced a lower average delay than those of Airline B.

	Airline A (07/08/2006)	Airline B (07/08/2006)	Airline A (07/12/2006)	Airline B (07/12/2006)
Average delays of disrupted passengers (minutes)	261.76	409.39	482.99	578.25
*Percentage of disrupted passengers recovered by the airline on the same day	45.87%	36.62%	36.08%	29.45%
Average delays of disrupted passengers recovered by the airline on the same day (minutes)	149.77	218.55	240.75	290
*Percentage of disrupted passengers recovered by other airlines	44.50%	41.07%	39.54%	34.64%
Average delays of disrupted passengers recovered by other airlines (minutes)	265.36	356.08	446.9	503.46
*Percentage of disrupted passengers experiencing overnight delays	7.80%	20.61%	24.38%	35.91%
Average delays of disrupted passengers experiencing overnight delays (minutes)	900	888	900	886.8
*Percentage of disrupted passengers who were rebooked to earlier flights	1.83%	1.69%	0.21%	0. 85%
*Percentage of diverted passengers	0	0.21%	1.60%	0.21%

Table 5-7: Degrees of passenger disruptions (* out of all disrupted passengers)

The above facts and their corresponding outcome (that Airline B had a much higher ratio of disrupted passenger delay to operated flight delay than did Airline A) are rooted in the difference in the level of connecting service at Airline A's major airports and at Airline B's major airports. Because Airline A concentrates flight operations at its three major hubs more than Airline B does at its major airports (which spreads its flight operations among many airports), when a disruption occurs, Airline A has more alternative flights to re-accommodate the disrupted passengers. To summarize, fewer recovery alternatives provided by Airline B itself, together with the longer average waiting time for an alternative itinerary made the average disrupted passenger delay higher for Airline B than Airline A. We conclude that, the multiplier which equalizes flight delay and passenger delay are airline dependent. Further, the difference in the values of this multiplier between Airline A and Airline B indicates that flight-specific on-time performance metrics that ignore airline heterogeneity might be an inaccurate measure of passenger experiences. Based on our results, a better on-time performance metric should: (1) take into account carrier-specific characteristics; and (2) reflect passenger delay.

Highlight Finding 3 – The Impact of Traffic Levels

Due to a weaker economy and soaring fuel costs, some airlines recently announced capacity cuts. For example, in June 2008, American Airlines said it plans to shed capacity by as much as 12% in the fourth quarter of this year. Chicago, Dallas, and LaGuardia will feel the biggest effects after American's action (The New York Times, June 26, 2008). Similarly, Frontier Airlines has cut its mainline capacity by 17% from September through March in 2008 (Yahoo Finance, June 25, 2008). Rather than reducing capacity, Northwest Airlines has responded to the situation by cancelling two routes to Europe and suspending another in October 2008. The routes being canceled are Detroit-Dusseldorf and Hartford-Amsterdam, and the Minneapolis/St Paul-Paris service will be suspended through March (Market Watch, June 26, 2008). At the same time, Southwest Airlines is adding service in high-demand markets (for example, Denver) to take advantage of other carriers' capacity cuts. With its hedging program, Southwest is able to pay less for fuel than most of its rivals (The Wall Street Journal, June 26, 2008).

With these trends in the current airline industry, we expect significant changes in airport traffic and airline route structures. In this thesis, we develop a methodology to evaluate, on an on-going basis, changes in the underlying aviation market. Unlike previous studies, the framework developed in this thesis is not restricted by the availability of proprietary airline data and can be adopted to estimate itinerary-based passenger demand and delays for any US airline included in the BTS database.

Underlying our study, there are two scenario representations, which pertain to various levels of airport traffic under different weather conditions. The "low-delay" day "mimics" a scenario with good weather and low levels of flight operations for both airlines. As a second scenario, on the "high-delay" day, Airline A experienced a number of flight cancellations and higher delays caused by adverse weather conditions in the

East Coast (8% extreme weather delay and 48% NAS delay). These delays along with increasing flight operations resulted in significant capacity reductions at affected airports. The changes in flight and passenger delay statistics from July 8 to July 12, 2006 for each airline (Table 5-8) reflect the impact of increasing flight traffic on passenger delays and disruptions when airport capacities are reduced by poor weather conditions for different airlines. Based on Table 5-8, we divide the changes in average delay by the percentage increase in flight operations and obtain the following results:

- For Airline A, an increase in flight operations of one percent corresponds to an increase in the average operated flight delay (average delay of flights with positive delays) of 18.9% (9.1%). For Airline B, an increase in flight operations of one percent corresponds only to an increase in average operated flight delay (average delay of flights with positive delays) of 10.3% (3.1%).
- For Airline A, an increase in flight operations of one percent corresponds to an increase in overall passenger delay (average delay of passengers with positive delays) of 20.9% (8.5%). For Airline B, an increase in flight operations of one percent corresponds only to an increase in overall passenger delay (average delay of passengers with positive delays) of 9.5% (4.4%).
- For Airline A, an increase in flight operations of one percent corresponds to an increase in percentage of disrupted passengers (average disrupted passenger delay) of 22.2% (3.1%). For Airline B, an increase in flight operations of one percent corresponds only to an increase in percentage of disrupted passengers (average disrupted passenger delay) of 12.3% (2.7%).

The above statistics suggest that under poor weather conditions, increasing flight operations at busy airports, compared to non-congested airports, can cause a much greater increase in passenger delay and disruptions when airport capacity is reduced by adverse weather condition. This impact is most pronounced with the numbers of disrupted passengers. In our case, Airline A suffered almost twice as much increase in the number of passenger disruptions as Airline B.

	Airline A	Airline B
1. Number of flight operations (domestic)	**27%**	**15%**
2. Number of onboard passengers (on domestic flights, in thousands)	**44%**	**6%**
3. Average load factor per flight leg	**-2%**	**-8%**
Average Flight Delay (F-Delay)		
4. 15 minutes on time performance (*15-OTP*)	**-31%**	**-15%**
5. Percentage of delayed flights (only flights operated)	**218%**	**120%**
6. Percentage of cancelled flights	**NA**[14]	**102%**
7. Average delay of operated flights (minutes)	**509%**	**155%**
8. Average delay of flights with delays (minutes)	**247%**	**47%**
Average Passenger Delay (P-Delay)		
9. Average delay of all passengers (minutes)	**564%**	**143%**
10. Percentage of delayed passengers	**104%**	**82%**
11. Percentage of disrupted passengers	**600%**	**184%**
12. Average delay of non-disrupted passengers (minutes)	**467%**	**183%**
13. Maximum delay of non-disrupted passengers (minutes)	**147%**	**119%**
14. Average delay of disrupted passengers (minutes)	**85%**	**41%**
15. Average delay of delayed passengers (minutes)	**230%**	**66%**

Table 5-8: Changes (%) in passenger and flight delay statistics from July 8 to July 12 in 2006

[14] The legacy carrier had zero flight cancellations on July 8, 2006 and 1.52% of its flights cancelled on July 12.

Highlight Finding 4 – The Impact of Independent Delay on Passenger Delay

Figure 5-12 and Figure 5-13 depict the cumulative distributions of passengers with delays greater than or equal to a certain value. Figure 5-14 and Figure 5-15 depict the cumulative distributions of *disrupted* passengers with delays greater than or equal to a certain value. Note that the horizontal gap between the solid curve (July 8, 2006) and the dashed curve (July 12, 2006) represents the difference in delays for a fixed percentage of passengers. The vertical gap between the solid curve and the dashed curve represents the difference in the percentage of passengers for a fixed delay. As seen from these plots, Airline A has much greater horizontal and vertical gaps than does Airline B. Once again, this shows on July 12, 2006, a "high-delay" day for both airlines in terms of flight operations, Airline A suffered more passenger delay than Airline B. This outcome is not because Airline A does not plan enough turn time slack (in fact, the opposite is evidenced by its lower percentage of flights with propagated delay despite that it had longer average delay per flight). Rather, it is attributable to the higher values of independent delay, most of which are due to weather and air traffic control (ATC). Hence, the only thing Airline A can do to improve on-time performance is to increase its block time. However, for the magnitude of independent delay it can experience on high-delay days, increasing block time would be prohibitively expensive and cause unacceptably long scheduled travel times for passenger.

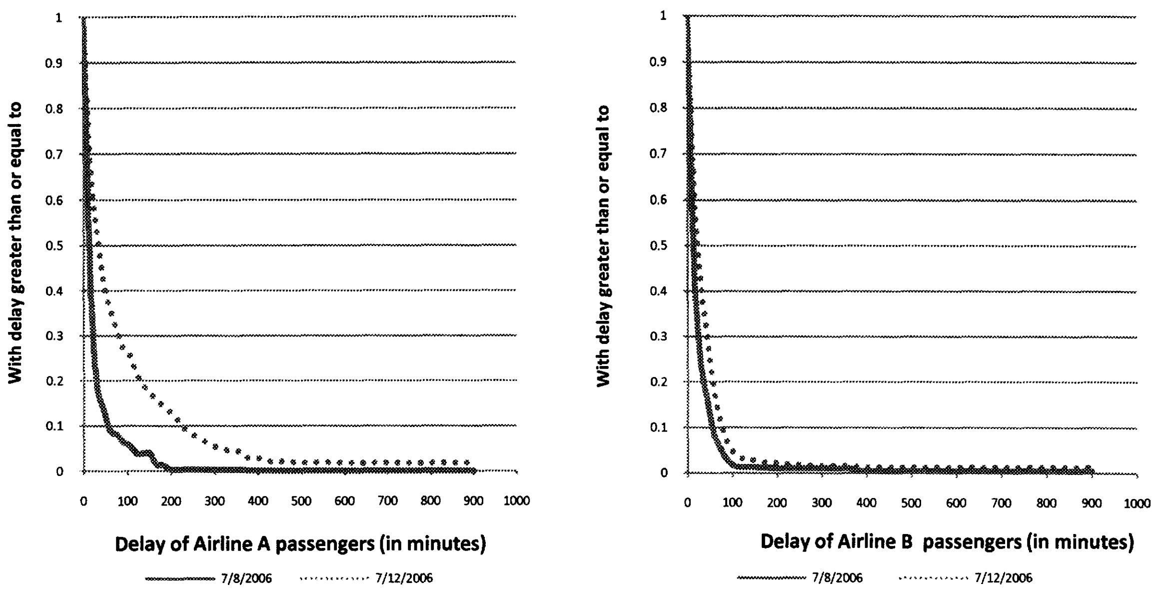


Figure 5-12: Cumulative distributions of passenger delays
(among all delayed passengers)

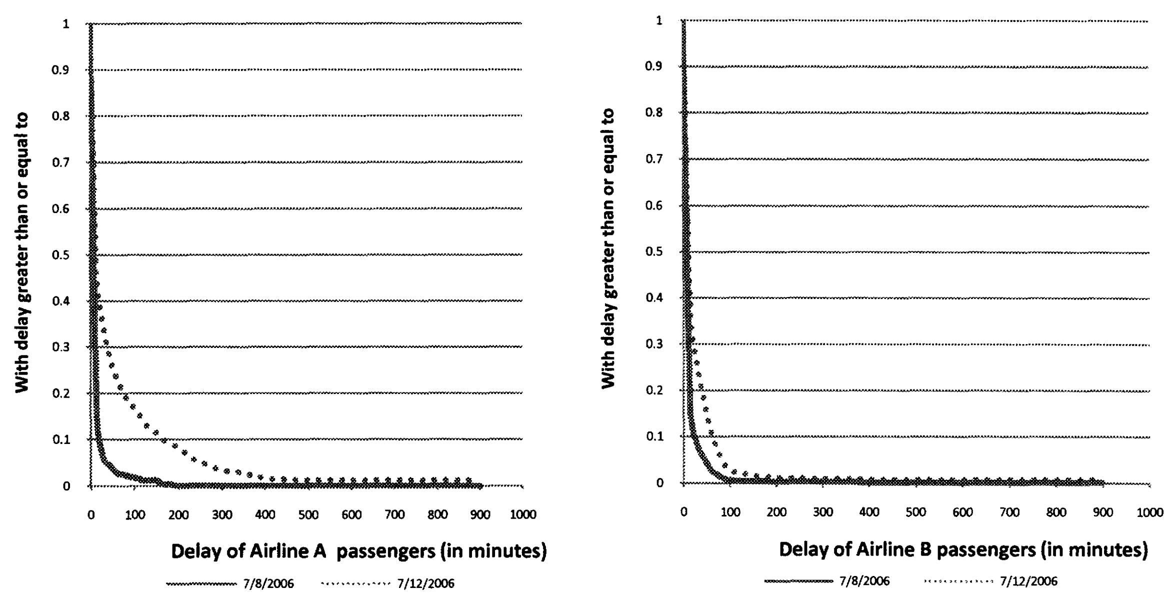


Figure 5-13: Cumulative distributions of passenger delays
(among all passengers)

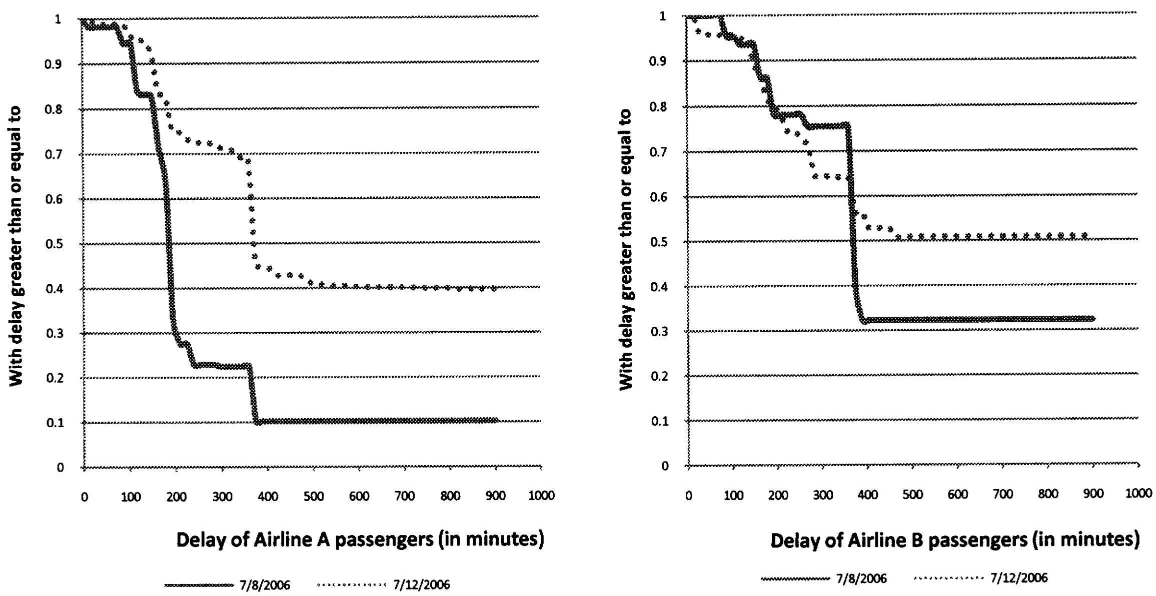


Figure 5-14: Cumulative distributions of *disrupted* passenger delays (among disrupted passengers)

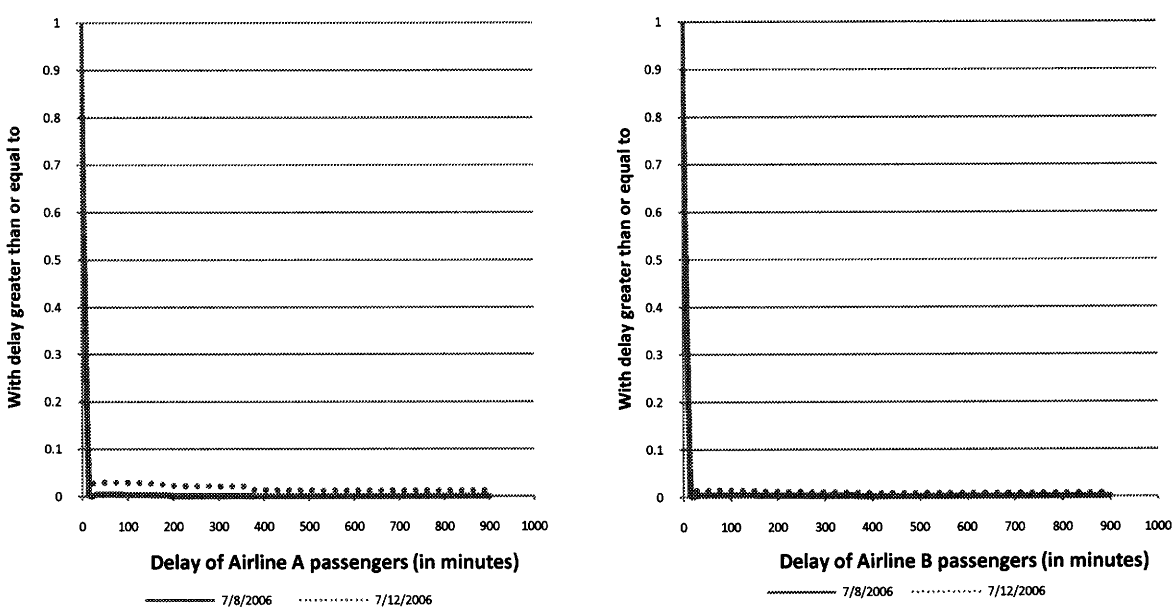


Figure 5-15: Cumulative distributions of *disrupted* passenger delays (among all passengers)

5.5 Passenger Disruption Analysis

Recognizing the significance of disrupted passengers in understanding passenger delays and schedule performance, we further investigate the characteristics that influence the degree of disruption, such as time-of-day, as well as departing and connecting airports. Table 5-9 lists the percentages of disrupted passengers caused by flight cancellations and missed connections, respectively.

	Airline A (07/08/2006)	Airline B (07/08/2006)	Airline A (07/12/2006)	Airline B (07/12/2006)
Percentage of disrupted passengers	**0.40%**	**0.44%**	**2.80%**	**1.25%**
Percentage of passengers on cancelled flights	**0**	**0.09%**	**1.03%**	**0.91%**
Percentage of passengers missing connections	**0.40%**	**0.35%**	**1.77%**	**0.34%**

Table 5-9: Disrupted passengers due to flight cancellations and missed connections

From Table 5-9, the following observations are made:

- On July 8, 2006, the majority of disrupted passengers were due to missed connections as both airlines had very low cancellation rates (in the case of Airline A, the cancellation rate was 0). The percentage of disrupted passengers due to missed connections for Airline B was slightly lower than that for Airline A.
- On July 12, 2006, for Airline A, 36.79% of disrupted passengers were due to cancellations and 63.21% due to missed connections.
- On July 12, 2006, for Airline B, 72.80% of disrupted passengers were due to cancellations and 27.20% due to missed connections.

Explanations of the Above Observations

Notice on both days, missed connections caused the majority of passenger disruptions for Airline A (100% on July 8, 2006 and 63.21% on July 12, 2006). In addition, on July 12, the percentage of disrupted passengers due to missed connections for Airline A was 5.21 times greater than that for Airline B. Our estimates show that the overall passenger mix of Airline A (Airline B) is 35% (48%) connecting passenger traffic and 65% (52%) local passenger traffic. Moreover, the average passenger connecting time for Airline A's passengers was 97.87 (99.41) minutes compared to 134.65 (135.29) minutes for Airline B on July 8 (July 12), 2006. Hence, the greater percentage of passengers who misconnected on Airline A compared to Airline B can be explained by longer delays per flight and shorter connecting times.

Time of Disruptions

The time at which disruptions occur has an important impact on passenger delay. Past studies have shown that passenger delay can be more affected by the time of disruption than route frequency (Bratu and Barnhart (2005) [3]). Late disruptions leave limited options to re-accommodate the resulting group of disrupted passengers. Therefore, passengers with disruptions later in the day tend to experience greater delays than those with earlier disruptions. In Figure 5-16, we depict the total number of disruptions occurring in each two-hour window for both airlines on July 8 and July 12. We observe:

- The majority of Airline A's disruptions happened during the later part of both days. Moreover, Airline A had a significant percentage of passengers connecting during the later part of the day at its major hubs. As shown in Figures 5-2 and 5-3, the highest percentage of connecting passenger traffic happened from 9:00pm to 9:59pm at both Hub 1 (81% of passengers are connecting) and Hub 2 (73% of passengers are connecting). The late-in-the-day cancellations and delays left limited time for Airline A to re-accommodate the disrupted passengers who missed their connections or encountered a cancelled flight.

- On July 8, 2006, Airline B had the highest number of disruptions between 8am and 10am, with flights cancelled during those two hours. In contrast, on July 12, most of Airline B's passenger disruptions occurred during the later part of the day, where disruptions mainly arose from cancelled flights caused by carrier problems.

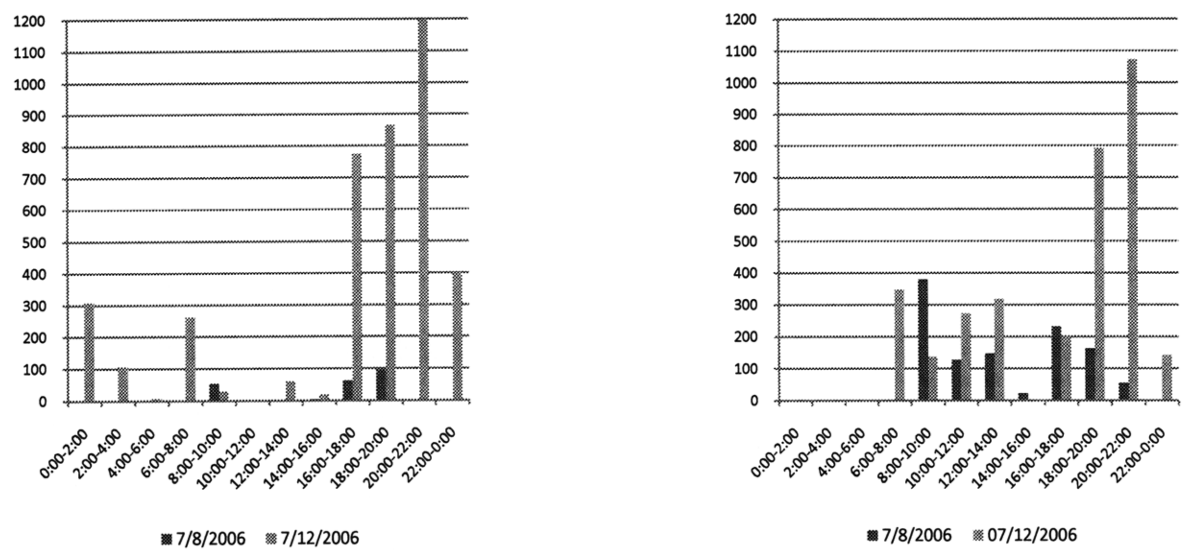


Figure 5-16: Number of disrupted passengers in each two-hour time window

(Left: Airline A, Right: Airline B)

5.6 Disruption Analysis by Airport

5.6.1 Aggregating Disruptions by Airport

Aggregating disrupted passengers by airport provides useful information on the number of disrupted passengers at different airports within the airline's system. Figure 5-17 to Figure 5-22 give the percentages of disrupted passengers at different airports. Airline A (Airline B) has a total of 12 (30) airports contributing passenger disruptions and we index these airports from 1 to 12 (1 to 30). For Airline A, hub airports are 1, 2, and 3. For Airline B, "hub" airports are 1, 2, 4, 6, and 9. For both airlines, the major airports had a large number of disrupted passengers. This makes sense because these airports have higher passenger shares compared to the secondary airports. However, we observe that Airline A's hubs experienced passenger disruptions to a greater extent percentage-wise than did Airline B's major airports. In contrast to Airline A, Airline B's disruptions are spread out among many more airports. We also observe that for Airline A, the three hubs had the highest percentages of disrupted passengers on both days. For Airline B, however, some secondary airports had higher percentages of disrupted passengers than did the major airports. This indicates that passenger disruptions are more related to airport congestion levels rather than airport passenger shares.

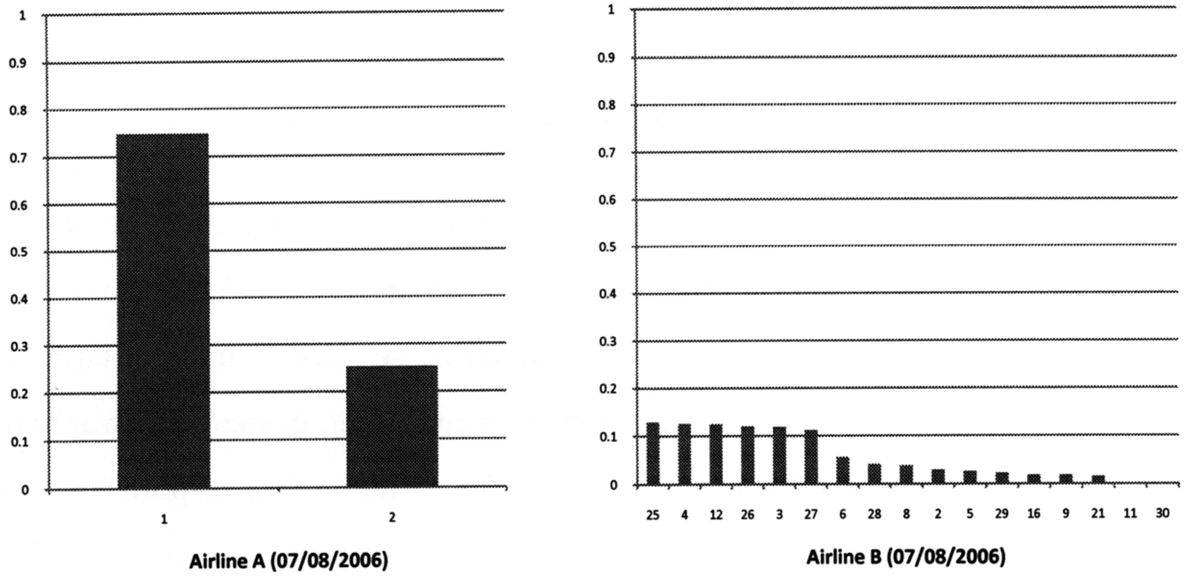


Figure 5-17: Percent of disrupted passengers at different airports on July 8

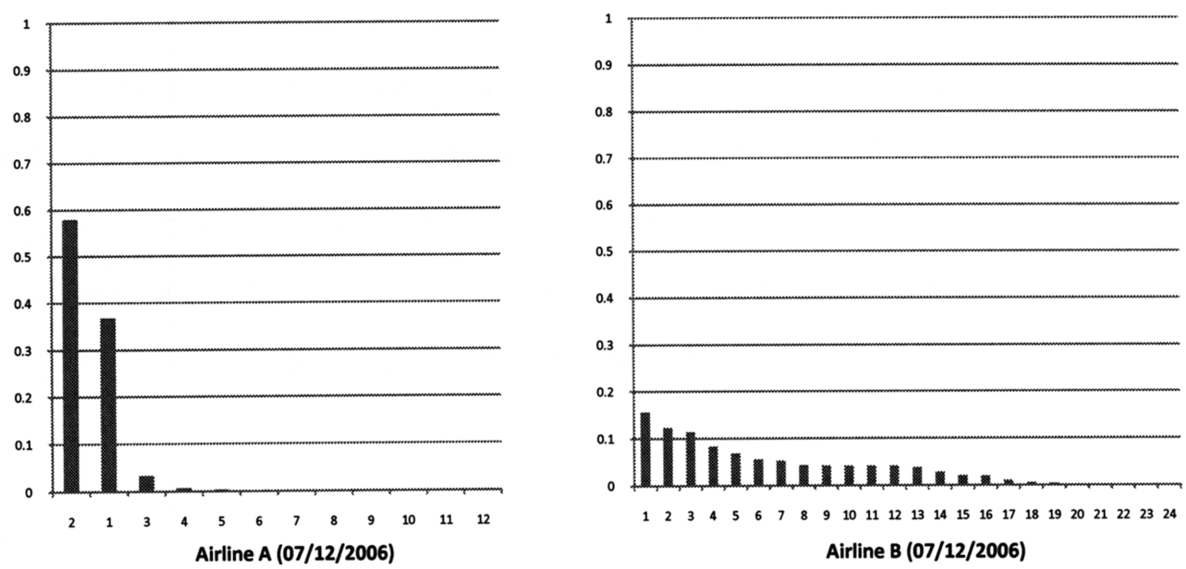


Figure 5-18: Percent of disrupted passengers at different airports on July 12

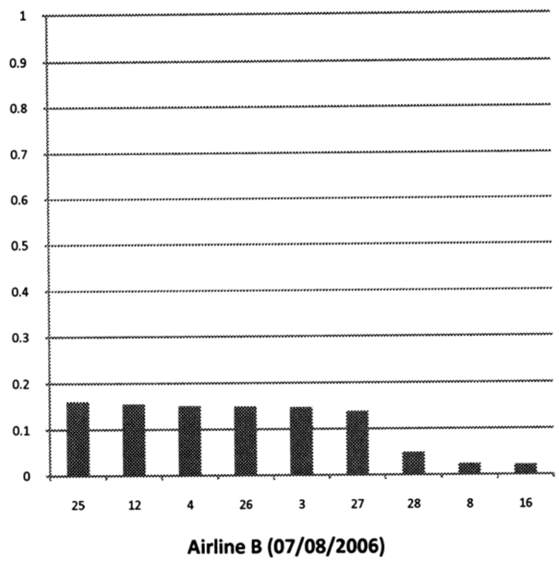


Figure 5-19: Percent of disrupted passengers due to cancelled flights at different airports of Airline B on July 8[15]

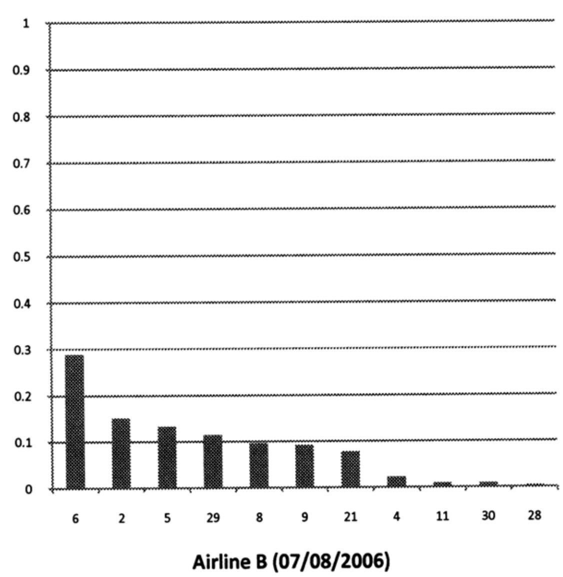


Figure 5-20: Percent of disrupted passengers due to missed connections at different airports of Airline B on July 8

[15] Airline A had no flights cancelled on July 8, 2006. Hence, the number of disrupted passengers due to cancelled flights was zero and the number of disrupted passengers due to missed connections was the same as Figure 5-17.

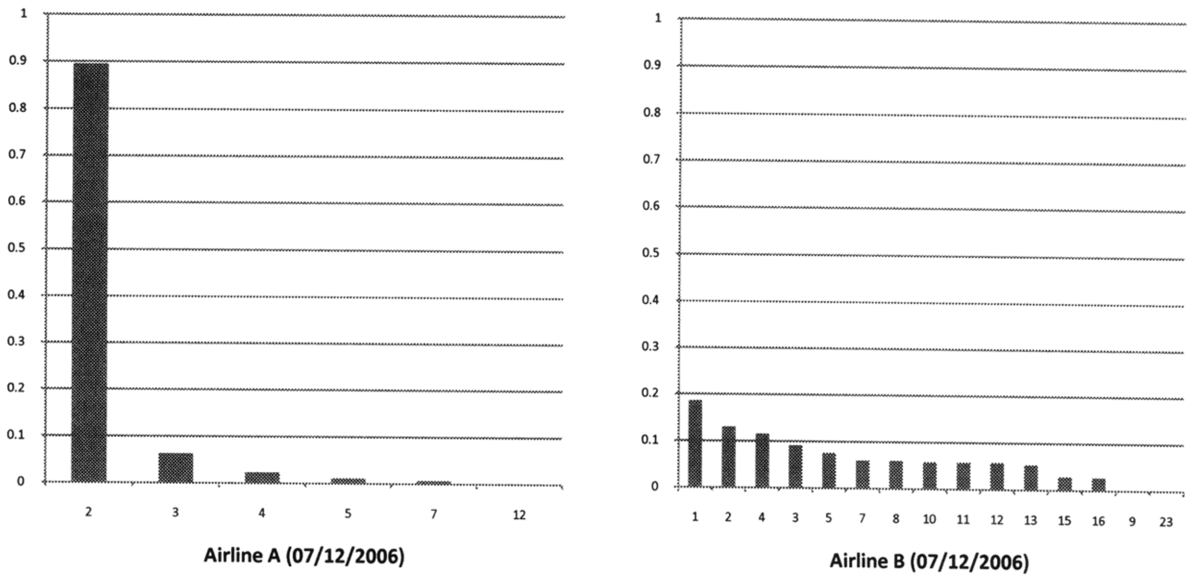


Figure 5-21: Percent of disrupted passengers due to cancelled flights at different airports on July 12

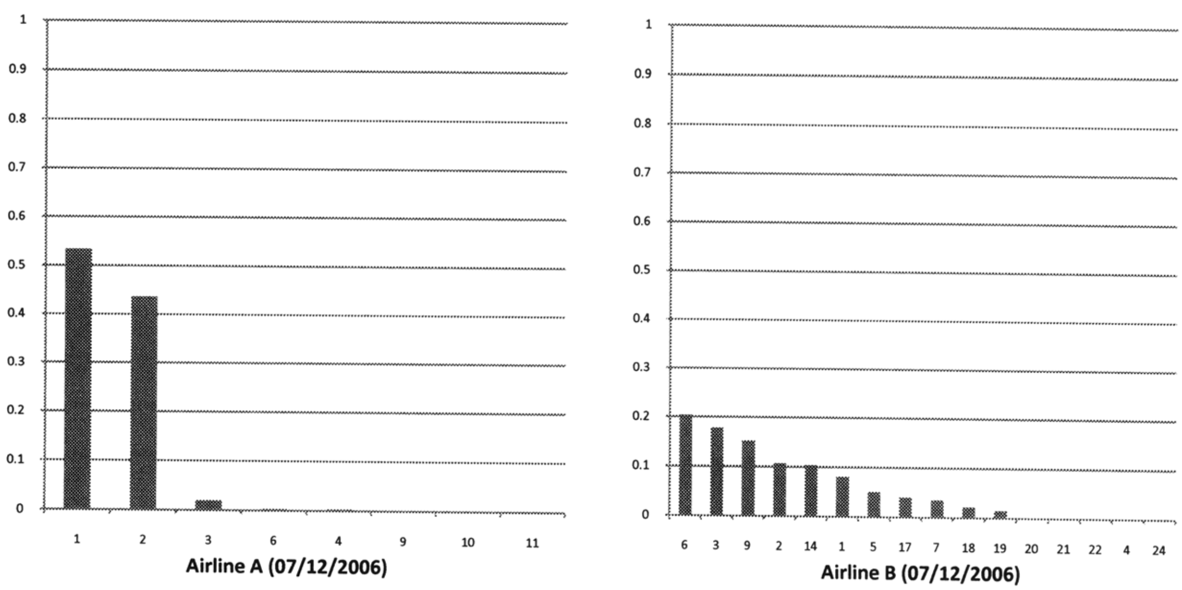


Figure 5-22: Percent of disrupted passengers due to missed connections at different airports on July 12

5.6.2 Percentage of Disruptions by Airport

In the following analysis, we compute: (1) the percentage of all disrupted passengers; (2) the percentage of disrupted passengers due to flight cancellations; and (3) the percentage of disrupted passengers due to missed connections, attributed to the different airports of each airline on July 8 and July 12, respectively (shown in Figure 5-23 to Figure 5-28). For passengers with missed connections, the airport that causes the disruption is not necessarily the same as the disruption location. For example, consider Passenger p on a 2-leg itinerary A-B-C, whose first leg f (A-B) departs 1 hour after the scheduled departure time. The total delay experienced by f (A-B) is 1 hour and 10 minutes, where the additional 10 minutes may be due to a wait-to-land at Airport B and/or longer flying time than scheduled. In this case, Passenger p misses his/her connection and is disrupted at Airport B mainly due to the departure delay at Airport A. We therefore claim that the disruption is mainly attributable to Airport A. If f (A-B) departs only 10 minutes after the scheduled time, however, but must wait for an hour after it is ready to land at Airport B, we say the disruption is mainly attributable to Airport B. Therefore, when a disruption is due to a missed connection, the following rule is adopted to decide the percentage of the disruption attributed to its corresponding late departure and late arrival, respectively:

First, we compute the total delay (TD) of f (A-B) at Airport B, which is defined as

$$\text{TD}\ (f\,(\text{A-B})) = \text{AAT}\ (f\,(\text{A-B})) - \text{PAT}\ (f\,(\text{A-B})),$$

where AAT represents the actual arrival time and PAT the planned arrival time.

Second, we compute the total departure delay (TDD) of f (A-B) at Airport A, which is

$$\text{TDD}\ (f\,(\text{A-B})) = \text{ADT}\ (f\,(\text{A-B})) - \text{PDT}\ (f\,(\text{A-B})),$$

where ADT represents the actual departure time and PDT the planned departure time.

Last, we compute the percentage of delay at Airport B explained by the departure delay at Airport A as:

Percentage of D (f (A-B)) at Airport A = Max (100%, TDD (f (A-B)) / TD (f (A-B)))[16],

which is also the percentage of the disruption attributed to Airport A when a passenger misses his/her connection at Airport B. Hence, we compute the percentage of delay at Airport B caused by delay at Airport B as

Percentage of D (f (A-B)) at Airport B = 1- Percentage of D (f (A-B)) at Airport A,

which is also the percentage of the disruption attributed to Airport B when a passenger misses his/her connection at Airport B. If Percentage of D (f (A-B)) by Airport A is 60% of the total delay, we say 60% of the disruption is attributed to Airport A.

With such a rule, we observe the following:

- For Airline A, the majority of overall passenger disruptions resulted from Hub 2 and Hub 1. On July 8, 2006, these two airports caused all disruptions of Airline A. In particular, Hub 2 caused 25% of the disruptions and Hub 1 caused 75% of the disruptions. Furthermore, all disruptions on July 8 were due to missed connections. On July 12, 94.8% of disruptions resulted from these two airports. In particular, Hub 2 caused 58% of the disruptions and Hub 1 caused 36.8% of the disruptions. The third hub of Airline A, contributed only 3.4% of the disruptions and a non-hub airport contributed 0.7%. Furthermore, of disruptions due to flight cancellations, Hub 2 caused 89.5%, the non-hub airport 2.3%, and Hub 3

[16] It is possible for TDD to be greater than TD.

6.3%. Of disruptions due to missed connections, Hub 2 caused 43.51%, Hub 1 53.29%, and Hub 3 0.36%[17].

- These results for Airline A make sense because both Hub 1 and Hub 2 are very busy airports, with weather often impacting flight operations. Because the percentage of connecting passengers at Hub 1 for Airline A is much higher than at Hub 2 (Figures 5-2 and 5-3), Hub 1 has the majority of disruptions due to missed connections.
- In contrast to Airline A, Airline B's disruptions are spread out more evenly among airports. Another striking difference is that the major airports of Airline B did not contribute to the majority of passenger disruptions. This perhaps has to do with the fact that passenger traffic is distributed more evenly in Airline B's system, unlike Airline A's, where a much larger portion of passengers connect through its major hubs (c.f. Section 5.2), and the longer passenger connecting times in Airline B's operation. In addition, the relationship between the number of disruptions and a particular airport may be strengthened in a system like Airline A whose hubs tend to locate in very busy airports which are highly impacted by capacity reductions due to weather.

[17] The remaining 1.1% of passenger disruptions was from 7 other airports.

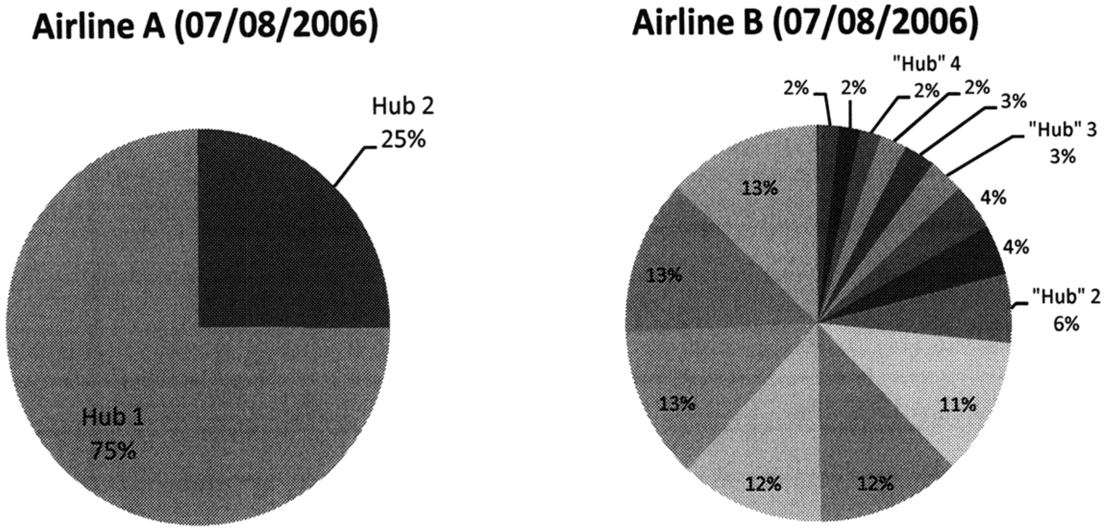


Figure 5-23: The percentage of disrupted passengers contributed by different airport

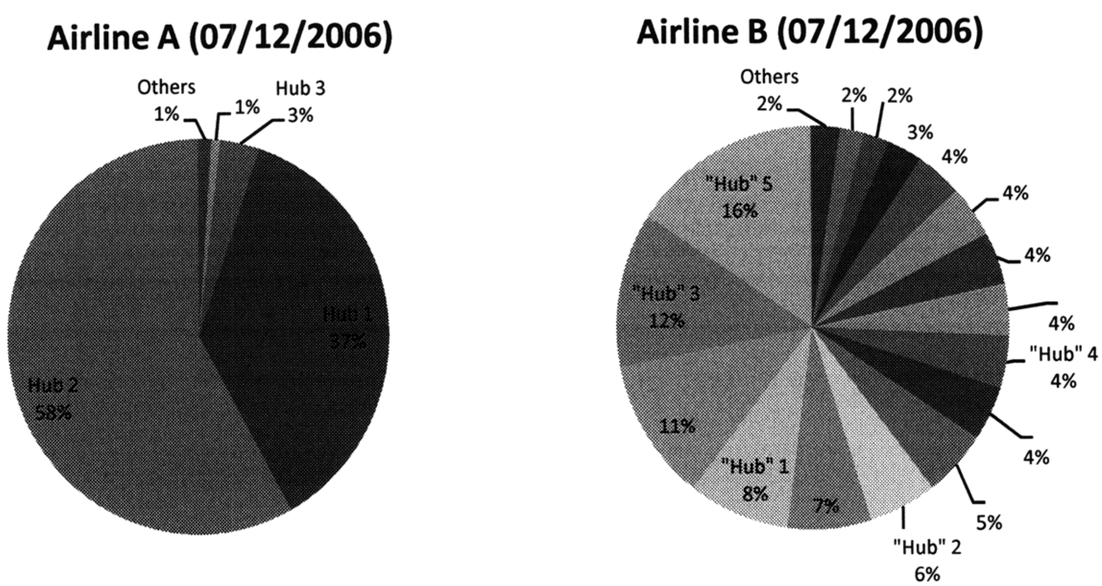


Figure 5-24: The percentage of disrupted passengers contributed by different airports

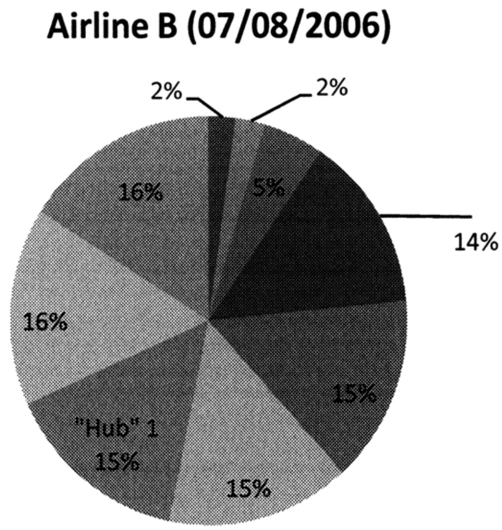
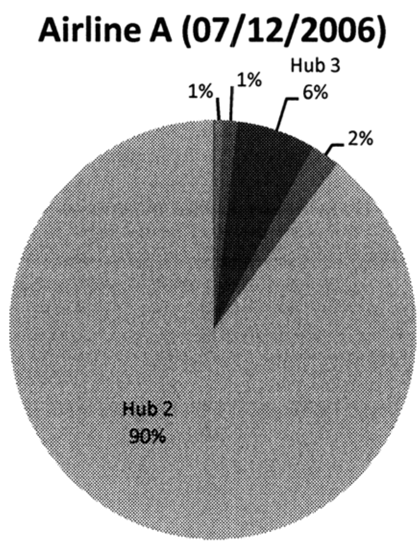


Figure 5-25: The percentage of disrupted passengers due to cancelled flights contributed by different airports[18]



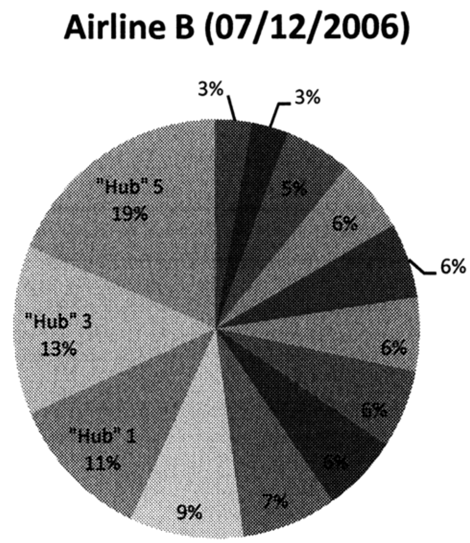


Figure 5-26: The percentage of disrupted passengers due to cancelled flights contributed by different airports

[18] Airline A had no flights cancelled on July 8, 2006 and the number of disrupted passengers due to cancelled flights was zero.

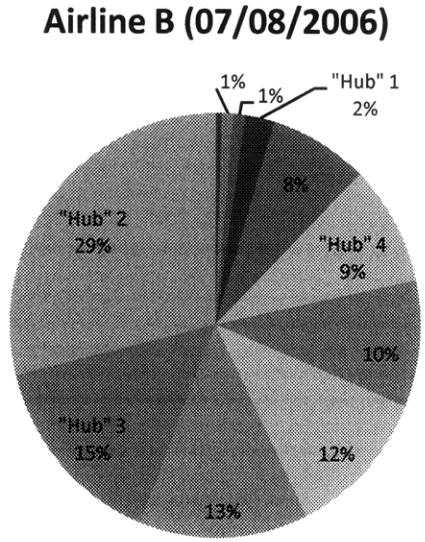
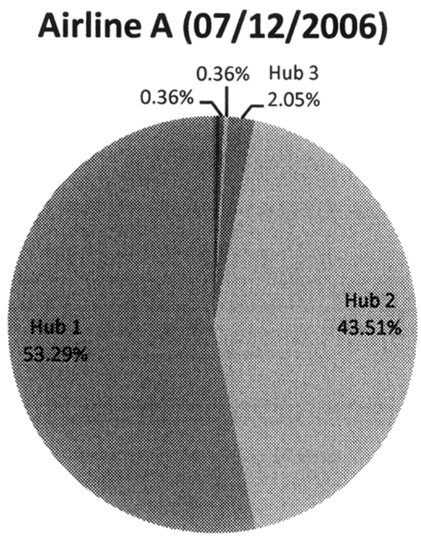


Figure 5-27: The percentage of disrupted passengers due to missed connections contributed by different airports[19]



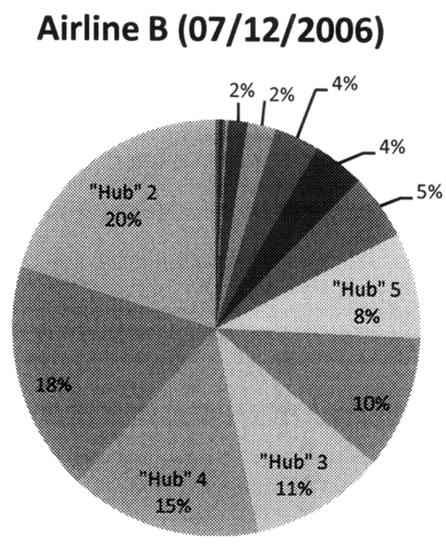


Figure 5-28: The percentage of disrupted passengers due to missed connections contributed by different airports

[19] Airline A had no flights cancelled on July 8, 2006. Hence, the number of disrupted passengers due to cancelled flights was zero and the number of disrupted passengers due to missed connections was the same as Figure 5-23 (left).

Summary of the Findings

Airline A has passenger operations concentrated in its three hubs, two of which are in the eastern US. As stated in Chapter 3.2.2, out of the fourteen flight cancellations, half of them were due to weather problems at airports located in the east. All cancellations of Airline B, however, arose from carrier problems rather than weather. A network carrier like A that concentrates its passenger operations at very busy airports can be at a disadvantage when weather adversely affects the hubs. Carriers like Airline B, in contrast, distribute passenger traffic more evenly in the system and thus are less impacted when some of the major airports suffer severe delays. Furthermore, as our analysis in Chapter 3.2.2 shows, Airline A suffered almost three times more NAS delay than Airline B (Figure 3-1 and Figure 3-2). On July 12, NAS delay accounted for nearly half of the total delay in Airline A's system while only 17% in Airline B's system. The difference in NAS delay is attributable to the fact that Airline A has a significant percentage of flights flying into or out of very busy hubs subjected to weather conditions and ground delay programs (GDP)[20]. This difference further explains why the major hubs of Airline A experienced a much higher number of passenger disruptions on the "high-delay" day than those of Airline B.

[20] The percentage of airports with GDPs is 39% for Airline A and 27% for Airline B. One of the major hubs of Airline A had the highest number of issued GDP's between 2007 and 2008 among all airports with ground holds, approximately 190. This implies a GDP was issued basically every other day at this airport with an average actual GDP duration of 505 minutes (Source: Metron Aviation).

Chapter 6

Conclusions

6.1 Summary Findings

This thesis aims to develop a framework for analyzing airlines' operational performances under different strategic decisions. A detailed study is conducted to compare differences between a major U.S. legacy carrier ("Airline A") and a major U.S. low-cost carrier ("Airline B") on two different days, a "low-delay" day and a "high-delay" day. We evaluate the impact of scheduling practices, network structures, passenger mix, and load factors on flight-based delays and on-time performances, and passenger delays and disruptions. The major components of this thesis consist of:

- Investigating the differences in the placement of slack time and other scheduling practices among the two types of airlines, and providing the rationale behind and effectiveness of these different strategies;
- Examining the sources of aircraft delays for the different airline types and identifying airport contributions to the delays experienced by these airlines;
- Developing a methodology to quantify passenger delays using publicly accessible data; and
- Comparing flight delays, passenger delays, and passenger disruptions between the two airlines with their different network structures and scheduling practices.

We conclude that differences in scheduling practices, network structure, and passenger mix result in differences in aircraft delays, and levels of passenger delays and disruptions. Hence, carrier-specific characteristics influence carrier performance and should be considered when designing on-time performance metrics. Characteristics that particularly affect the hub-and-spoke legacy carrier A are: (1) its hubs that experience heavy traffic volume, and are often subject to ground delay programs (GDPs) caused by poor weather conditions; and (2) its banked operations at two hubs, with a set of arriving flight legs scheduled closely with a set of departing flight legs to allow passenger connections between arriving and departing flight legs. Characteristics that particularly affect the low-cost carrier B are: (1) its flight network and passenger traffic is distributed more evenly across airports in the network; (2) it operates at a set of airports that are overall less congested than those of the major airports of legacy carrier A; and (3) its de-peaked (de-banked) flight schedule that provides longer passenger connection times on average, thereby reducing the chance of missed passenger connections.

In Chapter 2, we compare the scheduling practices of Airline A and Airline B and evaluate the resulting impact on flight on-time performance. This analysis is important because the way airlines buffer their schedules has a significant effect on flight on-time performance and passenger delays. We observe:

1. The legacy carrier A tends to plan more slack in its ground turn time while the low-cost carrier B tends to plan more slack in its block time. Furthermore, carrier B schedules almost identical amounts of turn time at each airport.
2. The differences between actual and planned turn times at different airports were more homogenous and smaller for the "high-delay" day for B, relative to those for carrier A.
3. The two airlines do not share many common arcs in their network operations. This implies carrier A and carrier B operate at different airports. Carrier A's major operations are at busier airports.

We believe the differences in schedule padding between the two airlines have to do with that Airline A operates banked hubs in which ground turn times, by necessity, must be longer on average to accommodate connecting passengers.

Airline B, however, operates de-banked hubs and schedules more rapid turns at airports to maximize productivity of aircraft and crews. To stem delay propagation and improve on-time performance, Airline B schedules, more slack in its block times.

In Chapter 3, we first compare flight delays and cancellations of the legacy carrier to those of the low-cost carrier. We observe:

1. On the "high-delay" day, extreme weather problems contributed 8% of the total delay to the legacy carrier's system while only 4% to the low-cost carrier's system.
2. The legacy carrier suffered almost three times as much NAS congestion delay than did the low-cost carrier. On the high delay day, NAS delay accounted for nearly half of the total delay in carrier A's network.
3. On the "high-delay" day, out of the fourteen flight cancellations of the legacy carrier, half of them were due to weather problems at four East Coast airports. All cancellations of the low-cost carrier, however, resulted from carrier problems rather than weather.

Additionally, we find that the overall 15-OTP performance of each airline is the sum over all airports of the average airport-specific 15-OTP weighted by the percentages of the airline's flights at that airport. This suggests that the extent of an airline's delays are impacted significantly by the airports at which they operate, independent of their scheduling practices, NAS delays being a distinguishing factor. NAS delays impact more significantly congested airports, and hence, NAS delays have more of an impact on Airline A than Airline B.

We decompose flight delays into "propagated delay" caused by late incoming flights and "independent delay" caused by issues attributable to airport congestion, carrier operations, NAS congestion, security, and/or extreme weather. We observe that:

1. The average IDD and IAD of the legacy carrier are significantly greater than those of the low-cost carrier on July 12, 2006, the "high-delay" day. Moreover, IDD plus IAD are together more than triple the propagated delay for the legacy carrier on that day. For the low-cost carrier, IDD plus IAD is almost double that of PD. The legacy carrier experienced twice as much average PD as the low-cost carrier on July 12; however, the percentages of flights experiencing delay propagation were higher for the low-cost carrier than for the legacy carrier on both days and the legacy carrier achieved a slightly lower average PD per flight (90% of the low-cost carrier's PD).
2. On July 8, 7 (4) airports accounted for 100% (80%) of the PD in the legacy carrier's network while 57 (23) airports did in the low-cost carrier's network. On July 12, 37 (12) airports accounted for 100% (80%) of the PD in the legacy carrier's network compared to 60 (27) airports in the low-cost carrier's network. We believe the fact that the low-cost carrier has delay propagation spread among many more airports than the legacy carrier is due to the low-cost carrier's scheduling practice of limiting turn time slack.
3. For both airlines, the majority of IDD, IAD, and PD were contributed by their major airports. However, when the aggregated delay statistics for July 12 are normalized by the number of flight operations at each airport, the magnitudes of independent delay were much less at the major airports of the low-cost carrier than at those of the legacy carrier. Specifically, the legacy carrier experienced 2.64 (2.99) times more average IDD (IAD) per flight at its three major hubs than did the low-cost carrier.

4. Both independent delay and propagated delay at two of the hubs of the legacy carrier were significantly greater on July 12, 2006, the "high-delay" day, than on July 8, 2006, the "low-delay" day. Between the "high-delay" day and "low-delay" day, the percent changes in independent delay and propagated delay of the low-cost carrier's major airports were much less compared to those of the legacy carrier.

We believe these differences are largely attributable to the fact that the legacy carrier has a higher percentage of flights connecting at congested airports that are often subject to weather conditions that reduce airport capacity. Most of the low-cost carrier's major airports are not as congested and not as impacted by reductions in capacity due to weather. When delays occur at the legacy carrier's airports, delay that propagates is likely to be larger than that of the low-cost carrier. However, more flights experience delay propagation for the low-cost carrier because there is little turn time slack in its operation and an arrival delay is likely to propagate to the next flight, unlike the legacy carrier, which has relatively more turn time slack. Further, on July 12, 2006, NAS delay accounted for almost half of total delay in the legacy carrier's system while it represented only 17% in the low-cost carrier's system.

Chapters 4 and 5 focus on passenger delay. In Chapter 4, we develop a 3-stage approach to estimate passenger demand and quantify passenger delay using only publicly available data. Our approach includes: (1) a search algorithm that generates itineraries; (2) a linear integer programming formulation that allocates passengers to the generated itineraries; and (3) a Passenger Delay Calculator (PDC) that computes passenger delay statistics. The major contribution of our methodology is that it provides a way to estimate passenger booking information for all scheduled flights using data from BTS.

In Chapter 5, we compare passenger delays and disruptions for the legacy carrier and the low-cost carrier. This chapter explores relationships between passenger delays and flight leg delays, cancellation rates, load factors, network structures, passenger mix, and schedule design. Our findings are as follows:

> Like the legacy carrier, the low-cost carrier exhibits a "hub" operation at its major airports. However, there is a difference in the level of connecting passenger traffic at the legacy carrier's major airports and at the low-cost carrier's major airports. Connecting passengers are distributed more evenly in the low-cost carrier's system and hence, the share of connecting passengers at the low-cost carrier's major airports is not as significant as that of the legacy carrier. Strictly speaking, "point-to-point" service is an inaccurate description of our low-cost carrier's network operations. Rather, the low cost carrier provides "hub-and-spoke" network service but with more "hubs" serving various levels of connecting passenger traffic in the network. The overall passenger mix of the legacy carrier (the low-cost carrier) is 35% (48%) connecting passenger traffic and 65% (52%) non-connecting passenger traffic.

Of the three major hubs of the legacy carrier, two of them are banked hubs, while the low-cost carrier has de-peaked schedules at its major airports. This explains why the low-cost carrier schedules shorter aircraft turns on average. By adding more slack into block time, the low-cost carrier is able to increase on-time arrival performance. The legacy carrier, however, schedules more slack in ground turn times so that flights can "catch" a bank at the hubs.

In terms of passenger delays, our results confirm findings from previous research that flight delays can severely underestimate delays of passengers who encountered cancelled flights or missed connections (namely, disrupted passengers). Several key differences between the two airlines in terms of passenger delay statistics are highlighted in the following:

1. We find that on July 12, 2006, the low-cost carrier had a higher percentage of flights with propagated delay than the legacy carrier but experienced much less passenger delay. The low-cost carrier can schedule its turn time with less slack and let delay propagate and still disrupt fewer passengers than the legacy carrier because the low-cost carrier offers longer connection times for its passengers than does the legacy carrier. As our analysis shows, the average passenger connecting time for the legacy carrier's passengers was 97.87 (99.41) minutes compared to 134.65 (135.29) minutes for the low-cost carrier on July 8 (July 12), 2006.
2. The ratios of passenger delay to operated flight delay for the low-cost carrier B were higher than the corresponding values for the legacy carrier A (Table 6-1). This difference is most pronounced in terms of the ratio of disrupted passenger delay to operated flight delay even though on the "high-delay" day, the percentage of disrupted passengers was much higher for carrier A than for the carrier B. Also on July 8 (July 12), 2006, for carrier A, the disrupted passengers experienced 35.8 (11.6) times more average delay than the non-disrupted passengers. For carrier B, the disrupted passengers experienced 81.4 (40.6) times more average delay than the non-disrupted passengers.

	Carrier A (07/08/2006)	Carrier B (07/08/2006)	Carrier A (07/12/2006)	Carrier B (07/12/2006)
Average delay of all passengers to average delay of operated flights	**1.28**	**1.81**	**1.38**	**1.73**
Average delay of disrupted passengers to average delay of operated flights	**41.16**	**84.94**	**12.46**	**47.09**

Table 6-1: Ratios of Passenger Delay to Flight Delay

The second observation indicates that the relationship between flight delay and passenger delay is far from being linear, but rather, a complex function of many airline-specific factors. The fact that the low-cost carrier had a much higher ratio of disrupted passenger delay to operated flight delay than did the legacy carrier is because:

> Unlike the legacy carrier (which concentrates flight operations at its three major hubs), the low-cost carrier spreads its flight operations among many airports. Therefore, when a disruption occurs, the low-cost carrier has fewer alternative flights to re-accommodate disrupted passengers than does the legacy carrier.

Having fewer recovery alternatives provided by the low-cost carrier itself results in longer average waiting times for an alternative itinerary and consequently longer delays for the low-cost carrier's disrupted passengers than for the legacy carrier's. From these facts, we conclude that the multiplier which equalizes flight delay and passenger delay are airline dependent. Further, the difference in the values of this multiplier between the legacy carrier and the low-cost carrier indicates that flight-specific on-time performance metrics that ignore airline heterogeneity can be an inaccurate measure of passenger experiences.

We find that under poor weather conditions, increasing flight operations at busy airports, compared to non-congested airports, can result in much greater increases in passenger delay and disruption. This phenomenon is most pronounced with the numbers of disrupted passengers. Supporting statistics are summarized in the following:

- For the legacy carrier, an increase in flight operations of one percent corresponds to an increase in the average operated flight delay (average delay of flights with positive delays) of 18.9% (9.1%). For the low-cost carrier, an increase in flight operations of one percent corresponds only to an increase in average operated flight delay (average delay of flights with positive delays) of 10.3% (3.1%).

- For the legacy carrier, an increase in flight operations of one percent corresponds to an increase in overall passenger delay (average delay of passengers with positive delays) of 20.9% (8.5%). For the low-cost carrier, an increase in flight operations of one percent corresponds only to an increase in overall passenger delay (average delay of passengers with positive delays) of 9.5% (4.4%).
- For the legacy carrier, an increase in flight operations of one percent corresponds to an increase in the percentage of disrupted passengers (average disrupted passenger delay) of 22.2% (3.1%). For the low-cost carrier, an increase in flight operations of one percent corresponds only to an increase in the percentage of disrupted passengers (average disrupted passenger delay) of 12.3% (2.7%).

The fact that the legacy carrier suffered more passenger delay than the low-cost carrier on the high-delay day is not because the legacy carrier does not plan enough turn time slack (in fact, the opposite is evidenced by its lower percentage of flights with propagated delay despite that it had longer average delay per flight). Rather, it is attributable to the higher values of independent delay, most of which are due to weather and air traffic control (ATC). Hence, the only thing the legacy carrier can do to improve on-time performance is to increase its block time. However, for the magnitude of independent delay it experiences, commensurate increases in block time would be prohibitively expensive and cause unacceptably long scheduled travel times for passenger. This suggests that airlines at congested airports subjected to weather and ATC delays cannot adequately adjust their planned schedules to avoid excessive delays at all times.

In terms of passenger disruption causes, we find that missed connections contributed the majority of passenger disruptions for the legacy carrier (100% on July 8, 2006 and

63.21% on July 12, 2006). In addition, on July 12, the percentage of disrupted passengers due to missed connections for the legacy carrier was 5.21 times greater than that for the low-cost carrier. The greater percentage of legacy carrier passengers who misconnected compared to the low-cost carrier can be explained by longer delays per flight, shorter connecting times, and larger percentages of passengers connecting.

For the legacy carrier, the majority of passenger disruptions occurred at its major hubs, while disruptions of the low-cost carrier were spread out more evenly among airports. Another striking difference is that the major airports of the low-cost carrier did not contribute the majority of disruptions. This perhaps has to do with the fact that passenger traffic is distributed more evenly in the low-cost carrier's system, in contrast to the legacy carrier, where a much larger portion of passengers connect through its major hubs. In addition, the relationship between the number of disruptions and a particular airport may be strengthened in a system like the legacy carrier whose hubs tend to locate in airports with high levels of congestion and frequent GDPs caused by poor weather conditions.

6.2 Future Directions

This thesis evaluates two major U.S. airlines on two different days to reveal the differences in scheduling practices, aircraft delays, and passenger delays and disruptions. In future work, more airlines and more days of operation should be studied to gain more insights into the passenger delays in the entire National Air Transportation System (NATS). Additionally, actual passenger enplanements from proprietary airline passenger data should be used to validate our findings.

Another limitation of this study is that in our PDC, we allow passengers to be rebooked on other airlines using a "rule-of-thumb" estimation in which schedules and passenger booking information for the other airlines is unknown. Therefore, an inaccurate estimate of disrupted passenger delays may occur in our approximation. Future work should consider explicitly itineraries of other airlines.

Future research should consider scenarios of various load factors and airline network structures and sensitivity analyses should be conducted. In Figure 6-1, we provide the scheme for future scenario and experiment development and sensitivity analyses.

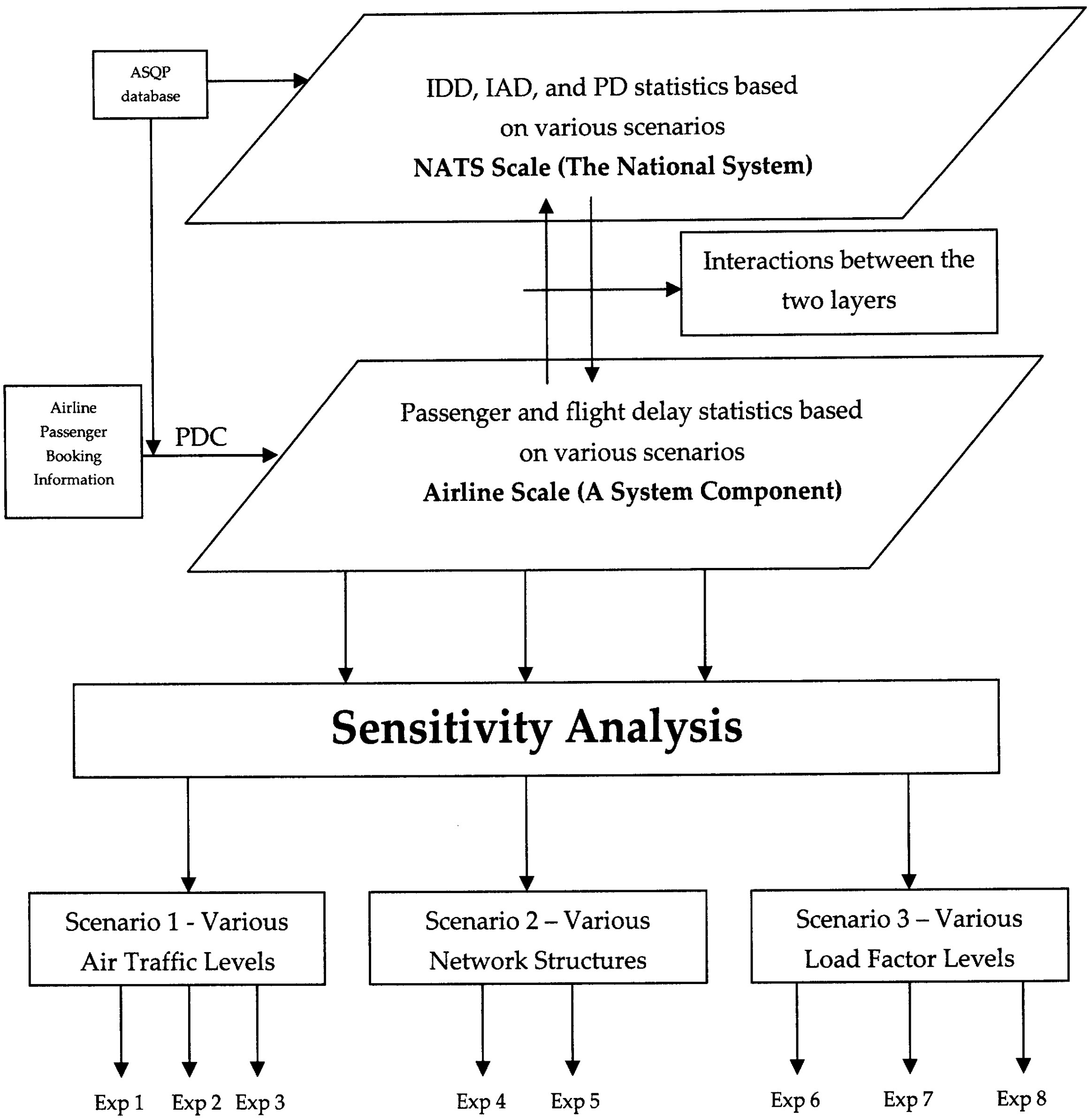


Figure 6-1: Scheme of the sensitivity analysis

BIBLIOGRAPHY

[1] Ball, M., Lovell, D., Mukherjee, A. Subramanian, B. (2005). Analysis of Passenger Delays: developing a passenger delay metric. *NEXTOR National Airspace System Performance Workshop*, Pacific Grove, CA

[2] Belobaba P., Simpson R. (1982) "Air Transportation Economics", Massachusetts Institute of Technology Flight Transportation Laboratory, unpublished.

[3] Bratu, S., Barnhart, C. (2005). An Analysis of Passenger Delays Using Flight Operations and Passenger Booking Data. *Journal of Transportation and Statistics, Number 1, Volume13, 1-27*

[4] Bureau of Transportation and Statistics (2006). Available: *http://www.transtats.bts.gov/carriers.asp*

[5] Bureau of Transportation and Statistics (2006a). Airline On-Time Performance Data (ASQP). Available: *http://www.transtats.bts.gov/Tables.asp?DB_ID=120&DB_Name=Airline%20On-Time%20Performance%20Data&DB_Short_Name=On-Time.*

[6] Bureau of Transportation and Statistics (2006b). Airline Origin and Destination Survey (DB1BCoupon). Available: *http://www.transtats.bts.gov/Tables.asp?DB_ID=125&DB_Name=Airline%20Origin%20and%20Destination%20Survey%20%28DB1B%29&DB_Short_Name=Origin%20and%20Destination%20Survey*

[7] Bureau of Transportation and Statistics (2006b). Airline Origin and Destination Survey (DB1BMarket). Available: *http://www.transtats.bts.gov/Tables.asp?DB_ID=125&DB_Name=Airline%20Origin%20and%20Destination%20Survey%20%28DB1B%29&DB_Short_Name=Origin%20and%20Destination%20Survey*

[8] Bureau of Transportation and Statistics (2006b). Airline Origin and Destination Survey (DB1BTicket). Available: *http://www.transtats.bts.gov/Tables.asp?DB_ID=125&DB_Name=Airline%20Origin%20and%20Destination%20Survey%20%28DB1B%29&DB_Short_Name=Origin%20and%20Destination%20Survey*

[9] Bureau of Transportation and Statistics (2006b). Form 41 Traffic T-100 Domestic Market Data. Available:
http://www.transtats.bts.gov/Tables.asp?DB_ID=110&DB_Name=Air%20Carrier%20Statistics%20%28Form%2041%20Traffic%29&DB_Short_Name=Air%20Carriers

[10] Bureau of Transportation and Statistics (2006b). Form 41 Traffic T-100 Domestic Segment Data. Available:
http://www.transtats.bts.gov/Tables.asp?DB_ID=110&DB_Name=Air%20Carrier%20Statistics%20%28Form%2041%20Traffic%29&DB_Short_Name=Air%20Carriers

[11] Caulkins J., Barnett A., Larkey P., Yuan Y., Goranson J. (1993) "The On-Time Machines: Some Analysis of Airline Punctuality", Operations Research Vol. 41(4), pp. 710-720

[12] Coldren, G. M., Koppleman, F. S., Kasturirangan, K., and Mukherjee, A. (2003) "Modeling aggregate air-travel itinerary shares: logit model development at a major US airline", *Air Transportation Management*, 9, 6, 361-369.

[13] Department of Transportation. Air Travel Consumer Report. Available:
http://airconsumer.ost.dot.gov/reports/index.htm

[14] Federal Aviation Administration. Aircraft Registration Database. Available:
http://www.faa.gov/licenses_certificates/aircraft_certification/aircraft_registry/releasable_aircaft_download/

[15] Federal Aviation Administration. Available:
http://www.fly.faa.gov/Products/AIS_ORIGINAL/shortmessage.html

[16] Gopalan R., Talluri K. (1998) "Mathematical Models in Airline Schedule Planning: A Survey," Annals of Operations Research 76, pp. 155-185.

[17] Hall, W. (1999) "Efficient Capacity Allocation in a Collaborative Air Transportation System," Massachusetts Institute of Technology, PhD Thesis.

[18] Heskett J., Jones T., Loveman G., Sasser E., and Schlesinger L. (1994) "Putting the Service-Profit Chain to Work," Harvard Business Review March-April.

[19] Janusewski S. (2002), "The Effect of Air Traffic Delays on Airline Prices", Working Paper, Massachusetts Institute of Technology Department of Economics.

[20] Lan S, Clarke J. P., and Barnhart C. (2006) "Planning for Robust Airline Operations: Optimizing Aircraft Routings and Flight Departure Times to Minimize Passenger Disruptions," Transportation Science, Vol. 40, No. 1, pp. 15-28.

[21] Massachusetts Institute of Technology. Airline Data Project. Available: *http://web.mit.edu/airlinedata/www/default.html*

[22] Mead K. (2001) *Flight Delays and Cancellations Continue as Major Sources of Customer Dissatisfaction*, Statement of the Inspector General, Department of Transportation, Washington, DC.

[23] Shumsky R. (1993) "The Response of The U.S. Air Carriers to the DOT's On-Time Disclosure Rule," Massachusetts Institute of Technology SM Thesis.

[24] Wang, D., Sherry, L., and Donohue, G. (2006). "Passenger Trip Time Metric for Air Transportation," *The 2nd International Conference on Research in Air Transportation.*

[25] Wang, D., Sherry, L., and Donohue, G. (2007). "Air Travel Consumer Protection: A Metric for Passenger On-Time Performance," 86th Annual Meeting of the Transportation Research Board, Washington DC.

[26] Wang, D., Sherry, L., and Donohue, G. (2007). "Trend Analysis of Airline Passenger Trip Delays," 86th Annual Meeting of the Transportation Research Board, Washington DC.