Development and Validation of a New Air Carrier Block Time Prediction Model and Methodology

Dissertation

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Robyn Olson Litvay, M.S.

Graduate Program in Aeronautical Engineering

The Ohio State University

2012

Dissertation Committee:

Professor Meyer Benzakein, Advisor
Professor Mo-How Herman Shen
Professor Gerald M. Gregorek
Professor Nawal K. Taneja
Copyright by

Robyn Olson Litvay

2012
ABSTRACT

Commercial airline operations rely on predicted block times as the foundation for critical, successive decisions that include fuel purchasing, crew scheduling, and airport facility usage planning. Small inaccuracies in the predicted block times have the potential to result in huge financial losses, and, with profit margins for airline operations currently almost nonexistent, potentially negate any possible profit. Although optimization techniques have resulted in many models targeting airline operations, the challenge of accurately predicting and quantifying variables months in advance remains elusive. The objective of this work is the development of an airline block time prediction model and methodology that is practical, easily implemented, and easily updated. Research was accomplished, and actual U.S., domestic, flight data from a major airline was utilized, to develop a model to predict airline block times with increased accuracy and smaller variance in the actual times from the predicted times. This reduction in variance represents tens of millions of dollars (U.S.) per year in operational cost savings for an individual airline.

A new methodology for block time prediction is constructed using a regression model as the base, as it has both deterministic and probabilistic components, and historic block time distributions. The estimation of the block times for commercial, domestic, airline operations requires a probabilistic, general model that can be easily customized for a specific airline’s network. As individual block times vary by season, by day, and by time
of day, the challenge is to make general, long-term estimations representing the average, actual block times while minimizing the variation.

Predictions of block times for the third quarter months of July and August of 2011 were calculated using this new model. The resulting, actual block times were obtained from the Research and Innovative Technology Administration, Bureau of Transportation Statistics (Airline On-time Performance Data, 2008-2011) for comparison and analysis. Future block times are shown to be predicted with greater accuracy, without exception and network-wide, for a major, U.S., domestic airline.
Dedicated to my family and friends for their love, support, patience, and humor.
ACKNOWLEDGMENTS

I wish to express my sincere gratitude to my adviser, Professor Meyer Benzakein, and the entire dissertation committee for their support and optimism. Thank you, especially, to Dr. Nawal K. Taneja for his true mentoring and guidance.

Additionally, I would like to extend my gratefulness to Southwest Airlines for their cooperation during this project. Specifically, thank you to Lonny Hurwitz, Alex Heinold, Jamie Iberra, and Bill Owen in the Southwest Airlines Integrated Operations Planning (Network Planning and Flight Scheduling) group. I’ve learned much during this project, and greatly appreciate their willingness to work with me.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>ii</td>
</tr>
<tr>
<td>Dedication</td>
<td>iv</td>
</tr>
<tr>
<td>Acknowledgments</td>
<td>v</td>
</tr>
<tr>
<td>List of Tables</td>
<td>viii</td>
</tr>
<tr>
<td>List of Figures</td>
<td>x</td>
</tr>
</tbody>
</table>

## Chapters

1.0 Introduction

1.1 Background and General Information                                1
1.2 Airline Master Schedule, Block Times, and Related Definitions     3
1.3 On-Time Performance and Block Time                                 5
1.4 Block Times and Fleet Type                                         9
1.5 Block Time Prediction and Historic Data                            10
1.6 Direct Routing, Block Time, and the FAA’s NextGen Program         11
1.7 RNP                                                                   14
1.8 RVSM                                                                   16
2.0 Computational framework

2.1 Block Times and Crew Scheduling

2.2 Predicting Components of Block Time

2.3 Block Time Prediction Modeling and Delay Propagation

2.4 Historic Block Time Distributions and Delays

2.5 Block Time Estimation

2.6 Block Time Prediction Factors and Foundation

2.7 Linear Relationship Validation and New Model Development

3.0 Results

3.1 New Model Results

3.2 Predicted vs. Actual Block Times: Summarized Data

3.3 On-Time Performance and Increased, Published Block Times

3.4 Specific Example of Increased Block Time Prediction Accuracy

3.5 Specific Example Actual Block Time Distributions and Results

4.0 Conclusions and recommendations

4.1 Financial Implications

4.2 Summary

4.3 Recommended Future Research

Bibliography

Appendix A
LIST OF TABLES

Table 1: On-Time Arrival Performance, National (January, 2011 - January, 2012) ........ 7

Table 2: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Mondays (June and July, 2011) .............................................................................. 44

Table 3: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Mondays (June and July, 2011) .............................................................................. 44

Table 4: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Tuesdays (June and July, 2011) .............................................................................. 46

Table 5: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Tuesdays (June and July, 2011) .............................................................................. 46

Table 6: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Wednesdays (June and July, 2011) .............................................................................. 47

Table 7: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Wednesdays (June and July, 2011) .............................................................................. 47

Table 8: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Thursdays (June and July, 2011) .............................................................................. 48

Table 9: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Thursdays (June and July, 2011) .............................................................................. 48
Table 10: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Fridays (June and July, 2011)........................................................................................................49

Table 11: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Fridays (June and July, 2011)........................................................................................................49

Table 12: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Saturdays (June and July, 2011)........................................................................................................50

Table 13: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Saturdays (June and July, 2011)........................................................................................................50

Table 14: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Sundays (June and July, 2011)........................................................................................................51

Table 15: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Sundays (June and July, 2011)........................................................................................................51

Table 16: Average Change in the Standard Deviation of Predicted Versus Actual Block Time Distributions Using the New Model.........................................................52

Table 17: 2010 Airline Direct Operating Costs per Minute.................................................78

Table 18: U.S. Airline Bankruptcies, 2000-2011.................................................................79
LIST OF FIGURES

Page

Figure 1: On-Time Arrival Performance, National (January, 2011 - January, 2012)........ 8

Figure 2: U.S. Airline Flight Delay Causes by Year .................................................. 8

Figure 3: Performance-Based Navigation: RNAV/RNP ..............................................13

Figure 4: Projected FAA NextGen Program Costs vs. Benefits.................................18

Monday, Short Haul Comparisons, Departures Before 1000

Figure 5: Southwest Airlines Predicted Block Times Minus Actual Block Times…….. 53

Figure 6: New, Predicted Block Times Minus Actual Block Times...........................54

Figure 7: New, Predicted Block Times +5 Minutes Minus Actual Block Times....... 55

Figure 8: New, Predicted Block Times +10 Minutes Minus Actual Block Times…… 56

Tuesday, Long Haul Comparisons, Departures After 0955 and Before 2000

Figure 9: Southwest Airlines Predicted Block Times Minus Actual Block Times…….. 56

Figure 10: New, Predicted Block Times Minus Actual Block Times....................... 57

Figure 11: New, Predicted Block Times +5 Minutes Minus Actual Block Times ....... 57

Figure 12: New, Predicted Block Times +10 Minutes Minus Actual Block Times…… 58
Wednesday, Long Haul Comparisons, Departures After 1955

Figure 13: Southwest Airlines Predicted Block Times Minus Actual Block Times…… 58

Figure 14: New, Predicted Block Times Minus Actual Block Times…………………… 59

Figure 15: New, Predicted Block Times +5 Minutes Minus Actual Block Times…… 59

Figure 16: New, Predicted Block Times +10 Minutes Minus Actual Block Times…… 60

Thursday, Short Haul Comparisons, Departures After 1955

Figure 17: Southwest Airlines Predicted Block Times Minus Actual Block Times…… 60

Figure 18: New, Predicted Block Times Minus Actual Block Times…………………… 61

Figure 19: New, Predicted Block Times +5 Minutes Minus Actual Block Times…… 61

Figure 20: New, Predicted Block Times +10 Minutes Minus Actual Block Time…… 62

Friday, Short Haul, Departures After 0955 and Before 2000

Figure 21: Southwest Airlines Predicted Block Times Minus Actual Block Times…… 62

Figure 22: New, Predicted Block Times Minus Actual Block Times…………………… 63

Figure 23: New, Predicted Block Times +5 Minutes Minus Actual Block Times……… 63

Figure 24: New, Predicted Block Times +10 Minutes Minus Actual Block Times……… 64

Saturday, Long Haul, Departures Before 1000

Figure 25: Southwest Airlines Predicted Block Times Minus Actual Block Times…… 64

Figure 26: New, Predicted Block Times Minus Actual Block Times…………………… 65
Figure 27: New, Predicted Block Times +5 Minutes Minus Actual Block Times……… 65

Figure 28: New, Predicted Block Times +10 Minutes Minus Actual Block Times……… 66

**Sunday, Short Haul, Departures After 0955 and Before 2000**

Figure 29: Southwest Airlines Predicted Block Times Minus Actual Block Times……… 66

Figure 30: New, Predicted Block Times Minus Actual Block Times…………………… 67

Figure 31: New, Predicted Block Times +5 Minutes Minus Actual Block Times……… 67

Figure 32: New, Predicted Block Times +10 Minutes Minus Actual Block Times……… 68

Figure 33: Distribution of OAKABQ All Southwest Airlines Flights, Actual Block Times, Third Quarter, 2009-2010…………………………………………………………… 69

Figure 34: SWA Distribution of OAKABQ Actual Block Times, Third Quarter, 2009 and 2010, 0615 Scheduled Departure Time………………………………………. 70

Figure 35: SWA Distribution of OAKABQ Predicted Block Times, Third Quarter, 2011, All Scheduled Departure Times……………………………………….. 71

Figure 36: Distribution of OAKABQ Actual Block Times, July and August, 2011, All Departure Times……………………………………………………………..72

Figure 37: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010……… 73

Figure 38: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010……… 74

Figure 39: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010……… 74

Figure 40: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010……… 75
Figure 41: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010………. 75

Figure 42: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010………. 76

Figure 43: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010………. 76

Figure 44: Distribution of OAKABQ All Southwest Airlines Flights, Actual Block Times, Third Quarter, 2009-2010……………………………………………….. 77

Monday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.1: Southwest Airlines Predicted Block Times Minus Actual Block Times…. 96

Figure A.2: New, Predicted Block Times Minus Actual Block Times………………. 96

Figure A.3: Southwest Airlines Predicted Block Times Minus Actual Block Times…. 97

Figure A.4: New, Predicted Block Times Minus Actual Block Times……………….. 97

Figure A.5: New, Predicted Block Times +5 Minutes Minus Actual Block Times ….. 98

Figure A.6: New, Predicted Block Times +10 Minutes Minus Actual Block Times ….. 98

Monday, Long Haul and Short Haul Comparisons, Departures After 0955 and Before 2000

Figure A.7: Southwest Airlines Predicted Block Times Minus Actual Block Times….. 99

Figure A.8: New, Predicted Block Times Minus Actual Block Times………………. 99

Figure A.9: Southwest Airlines Predicted Block Times Minus Actual Block Times… 100

Figure A.10: New, Predicted Block Times Minus Actual Block Times………………… 100
Monday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.11: Southwest Airlines Predicted Block Times Minus Actual Block Times…101

Figure A.12: New, Predicted Block Times Minus Actual Block Times ……………… 101

Figure A.13: Southwest Airlines Predicted Block Times Minus Actual Block Times….102

Figure A.14: New, Predicted Block Times Minus Actual Block Times………………….. 102

Tuesday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.15: Southwest Airlines Predicted Block Times Minus Actual Block Times .. 103

Figure A.16: New, Predicted Block Times Minus Actual Block Times………………….. 103

Figure A.17: Southwest Airlines Predicted Block Times Minus Actual Block Times... 104

Figure A.18: New, Predicted Block Times Minus Actual Block Times………………….. 104

Tuesday, Long Haul and Short Haul Comparisons, Departures After 0955 and Before 2000

Figure A.19: Southwest Airlines Predicted Block Times Minus Actual Block Times... 105

Figure A.20: New, Predicted Block Times Minus Actual Block Times………………….. 105

Figure A.21: Southwest Airlines Predicted Block Times Minus Actual Block Times... 106

Figure A.22: New, Predicted Block Times Minus Actual Block Times………………….. 106
Tuesday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.23: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 107

Figure A.24: New, Predicted Block Times Minus Actual Block Times ………………… 107

Figure A.25: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 108

Figure A.26: New, Predicted Block Times Minus Actual Block Times………………… 108

Wednesday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.27: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 109

Figure A.28: New, Predicted Block Times Minus Actual Block Times ………………… 109

Figure A.29: Southwest Airlines Predicted Block Times Minus Actual Block Times…110

Figure A.30: New, Predicted Block Times Minus Actual Block Times…………………110

Wednesday, Long Haul and Short Haul Comparisons, Departures After 0955 and

Before 2000

Figure A.31: Southwest Airlines Predicted Block Times Minus Actual Block Times .. 111

Figure A.32: New, Predicted Block Times Minus Actual Block Times ………………… 111

Figure A.33: Southwest Airlines Predicted Block Times Minus Actual Block Times….112

Figure A.34: New, Predicted Block Times Minus Actual Block Times………………… 112
Wednesday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.35: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 113

Figure A.36: New, Predicted Block Times Minus Actual Block Times …………………. 113

Figure A.37: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 114

Figure A.38: New, Predicted Block Times Minus Actual Block Times………………… 114

Thursday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.39: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 115

Figure A.40: New, Predicted Block Times Minus Actual Block Times………………… 115

Figure A.41: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 116

Figure A.42: New, Predicted Block Times Minus Actual Block Times………………… 116

Thursday, Long Haul and Short Haul Comparisons, Departures After 0955 and

Before 2000

Figure A.43: Southwest Airlines Predicted Block Times Minus Actual Block Times . 117

Figure A.44: New, Predicted Block Times Minus Actual Block Times …………………… 117

Figure A.45: Southwest Airlines Predicted Block Times Minus Actual Block Times.. 118

Figure A.46: New, Predicted Block Times Minus Actual Block Times………………… 118
Thursday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.47: Southwest Airlines Predicted Block Times Minus Actual Block Times . 119
Figure A.48: New, Predicted Block Times Minus Actual Block Times……………….. 119
Figure A.49: Southwest Airlines Predicted Block Times Minus Actual Block Times...120
Figure A.50: New, Predicted Block Times Minus Actual Block Times………………120

Friday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.51: Southwest Airlines Predicted Block Times Minus Actual Block Times.....121
Figure A.52: New, Predicted Block Times Minus Actual Block Times ………………. 121
Figure A.53: Southwest Airlines Predicted Block Times Minus Actual Block Times... 122
Figure A.54: New, Predicted Block Times Minus Actual Block Times………………122

Friday, Long Haul and Short Haul Comparisons, Departures After 0955 and Before 2000

Figure A.55: Southwest Airlines Predicted Block Times Minus Actual Block Times... 123
Figure A.56: New, Predicted Block Times Minus Actual Block Times………………123
Figure A.57: Southwest Airlines Predicted Block Times Minus Actual Block Times... 124
Figure A.58: New, Predicted Block Times Minus Actual Block Times………………124
Friday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.59: Southwest Airlines Predicted Block Times Minus Actual Block Times…125

Figure A.60: New, Predicted Block Times Minus Actual Block Times………………125

Figure A.61: Southwest Airlines Predicted Block Times Minus Actual Block Times…126

Figure A.62: New, Predicted Block Times Minus Actual Block Times………………126

Saturday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.63: Southwest Airlines Predicted Block Times Minus Actual Block Times…127

Figure A.64: New, Predicted Block Times Minus Actual Block Times ………………127

Figure A.65: Southwest Airlines Predicted Block Times Minus Actual Block Times….128

Figure A.66: New, Predicted Block Times Minus Actual Block Times………………128

Saturday, Long Haul and Short Haul Comparisons, Departures After 0955 and Before 2000

Figure A.67: Southwest Airlines Predicted Block Times Minus Actual Block Times .. 129

Figure A.68: New, Predicted Block Times Minus Actual Block Times………………129

Figure A.69: Southwest Airlines Predicted Block Times Minus Actual Block Times... 130

Figure A.70: New, Predicted Block Times Minus Actual Block Times………………130
Saturday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.71: Southwest Airlines Predicted Block Times Minus Actual Block Times...131

Figure A.72: New, Predicted Block Times Minus Actual Block Times.................. 131

Figure A.73: Southwest Airlines Predicted Block Times Minus Actual Block Times...132

Figure A.74: New, Predicted Block Times Minus Actual Block Times..................132

Sunday, Long Haul and Short Haul Comparisons, Departures Before 1000

Figure A.75: Southwest Airlines Predicted Block Times Minus Actual Block Times...133

Figure A.76: New, Predicted Block Times Minus Actual Block Times..................133

Figure A.77: Southwest Airlines Predicted Block Times Minus Actual Block Times...134

Figure A.78: New, Predicted Block Times Minus Actual Block Times.................. 134

Sunday, Long Haul and Short Haul Comparisons, Departures After 0955 and Before 2000

Figure A.79: Southwest Airlines Predicted Block Times Minus Actual Block Times...135

Figure A.80: New, Predicted Block Times Minus Actual Block Times..................135

Figure A.81: Southwest Airlines Predicted Block Times Minus Actual Block Times...136

Figure A.82: New, Predicted Block Times Minus Actual Block Times..................136
Sunday, Long Haul and Short Haul Comparisons, Departures After 1955

Figure A.83: Southwest Airlines Predicted Block Times Minus Actual Block Times...137

Figure A.84: New, Predicted Block Times Minus Actual Block Times..................137

Figure A.85: Southwest Airlines Predicted Block Times Minus Actual Block Times...138

Figure A.86: New, Predicted Block Times Minus Actual Block Times...................138
CHAPTER 1: INTRODUCTION

1.1 Background Information

The International Air Transport Association (IATA) reported in March of 2012 that the global aviation industry could anticipate financial losses in the range of USD5.3 billion for 2012, with rising fuel costs a primary contributor (IATA, 2012). On both local and worldwide scales, air transportation operators contend with a set of business and operating characteristics that few, if any, other industries experience. These characteristics, which include susceptibility to economic conditions, political climates, and weather abnormalities, in addition to the risks associated with any perishable product, contribute to the overall lack of profitability of the commercial airline industry as a whole (Taneja, 2008). Profit margins for any major airline in the United States (U.S.) are incredibly slim, and the International Air Transport Association (IATA) predicts a grim 0.8% gross net profit margin for commercial airlines in 2012 (IATA, 2011).

Operations research has worked to mitigate the many factors contributing to the lack of airline profitability through optimization of the many integrated systems making up and affecting their operations. As the components of an airline’s network are numerous and often include unpredictable variables, solution techniques may require computational abilities too large or too advanced to be practically implemented. Optimizing one system independently within an airline’s network often results in
detrimental effects on connected systems, or simply produces solutions that prove to be impractical. Sequentially optimizing multiple systems within a network is another technique, and benefits to airline operations have been gained using this approach. Cohn and Barnhart break airline schedule planning into core problems: “schedule design, fleet assignment, aircraft maintenance routing, and crew scheduling,” (Cohn and Barnhart, 2004, 4). These core problems are traditionally solved sequentially, as the number of variables and their interdependencies are too numerous and complex to integrate into a single model. As computing capabilities continue to increase, the ability to simultaneously consider the components comprising and affecting airline master schedules will also increase.

As fuel prices continue to rise, squeezing the tiny profit margins of some airlines and eliminating others, improved planning processes, predictions, and methodologies are increasingly important. This dissertation presents an investigation into the reduction of the variance in the predicted block time minus actual block time distributions for each and every city pair in the domestic network of a major, profitable, U.S. airline with the objective of optimizing operations at the network level. Prior to presenting the development of a prediction model to increase airline operations efficiency and minimize the connected, variable costs through more accurate block time predictions, relevant literature is reviewed, including explanations of airline operations and associated terminology. These previous works of other researchers are presented, and include recent academic and industry-developed models for airline operations predictions.
1.2 Airline Master Schedule, Block Times, and Related Definitions

Airline networks are created and developed to provide transportation services between markets, meaning airports serving a geographic area. The U.S. Department of Transportation (DOT) categorizes commercial airlines based on their gross annual revenues, not by aircraft size or profitability. A Major airline is defined in this context as one with an annual gross revenue exceeding $1 billion; a National airline is one with an annual gross revenue exceeding $100 million up to and including $1 billion; and a regional airline is one with an annual gross revenue less than or equal to $100 million (BTS, 2005). Examples of Major airlines include American Airlines, one of only a few surviving U.S. legacy carriers, and Southwest Airlines, considered to be the best example of a post-Deregulation airline in the U.S., today. Major airline networks in the U.S. have varied structures and sizes, but regardless whether an airline’s network is primarily constructed as hub-and-spoke, point-to-point, or a combination, a master flight schedule must be developed. The master flight schedule is reported to be the “most important product of an airline,” as it determines the markets to be served, targeted passengers, and, ultimately, profitability (Cohn and Barnhart, 2004, 4). A master schedule contains all flight segments, their scheduled departure and arrival times, time at the gate in-between flights (“turn” time), and scheduled aircraft maintenance time. Master schedule design, therefore, is the core challenge from which a commercial airline builds its success.

Block time, with respect to airline operations, is defined as the time beginning when an aircraft leaves the departure airport gate or parking position and ending upon its arrival at the destination airport gate or parking position. As such, block times include both the time to taxi for takeoff, the time airborne (flight time), and the taxi time after
landing to the gate. Flight time is defined as the time beginning at landing gear retraction after takeoff to touch down on the runway at the destination airport (BTS, 2010).

A late flight is defined by the U.S. Department of Transportation (DOT), Bureau of Statistics (BTS) as one departing or arriving fifteen minutes or more after its scheduled time (BTS, 2010). An airline must predict the block times for each city pair for which they provide service, and these predictions are, in turn, used to predict and estimate airport facilities requirements, gate utilization at each airport serviced, staffing and crew scheduling, passenger connection times, and aircraft maintenance scheduling. Fuel purchasing, which currently constitutes over 30% of an airline’s total operating costs (CAPA, 2011), also relies on predicted block times to estimate the quantity of fuel needed over time and many months in advance. An airline’s master schedule relies on accurate block times as a component of its objective function, which, in turn, is relied upon to predict fuel requirements. Inaccuracy across an airline’s network, with respect to predicting block times, represents millions of dollars (U.S.) per year in variable costs. Block time does not include the turn-around time, which is the time during which the aircraft is parked at the gate. Predicting block times is challenging, because most of the significant factors affecting these times are variable and subject to many influences and forces that are not controllable by the airlines, such as weather conditions, airport congestion, airspace congestion, air traffic control demands and capabilities, and seasonal variances. Accurately predicting block times allows for more accurate estimation of future airline fixed and variable costs, which provides a foundation for creating passenger fare structures.
A city pair is referred to as an origin and destination (O&D). Revenue is created through the demand for service between origin and destination airports either through non-stop, direct flights or through connecting flights. A flight segment is measured as the great circle distance from a single takeoff to a single landing between airports, and is referred to as its stage length. A non-stop, direct flight between a city pair is one flight segment, while a trip requiring multiple connections consists of multiple flight segments.

There is a predicted and actual block time for each, individual, flight segment.

1.3 On-Time Performance and Block Time

Airline on-time performance statistics are collected and published by the U.S. Bureau of Transportation Statistics (BTS), and are often misunderstood. Airlines publish scheduled arrival and scheduled departure times which reflect their estimated block times for each flight segment. Additional time, as a buffer against a possible late arrival, is a component of each, final, estimated block time, but the amount of additional time and how it is determined varies by airline. Provided a flight arrives at the intended destination airport gate less than 15 minutes after the airline’s published arrival time, the flight is considered to be “on time.” Adding too much extra time to an estimated block time as a buffer against a late arrival will negatively impact operations and increase costs, but there is no BTS statistical penalty when a flight arrives extremely early. Predicting the most accurate block times is the core of estimating the planned departure and arrival times for each flight, but deciding how much of a margin of time should be added to the predicted block times is also a significant challenge. One method is to select a time for
each flight leg that corresponds to a specific percentage point on the distribution of historic, actual block times occurring within a selected time period.

Published on-time performance data is a focal point of the U.S. media, and the larger the added time margin to the predicted block time, the less likely a flight will be published as late. Public perception of a poor on-time performance record negatively affects an airline’s passenger demand and reputation. The risk in adding too large a margin to predicted block times is that many flights will arrive extremely early at their destination. As resources, such as gates and ground personnel, are scheduled based on the published block times, aircraft arriving early may have to remain on the airport ramp with their engines continuing to run, waiting for a gate to become available. As actual block time is measured from gate to gate, a flight arriving early, but having to wait for a gate to become available, may have a recorded, actual block time that is not accurate. Although such a flight is officially recorded as “on time,” provided the parking gate becomes available less than 15 minutes after the scheduled arrival time, there is substantial, added cost accrued through burning extra fuel while waiting and through added variable crew costs. Additionally, passengers become frustrated when a flight arrives early, but they are trapped on the aircraft unable to deplane for more than a few minutes. Table 1 and figure 1 display the reported and published airline on-time performance statistics for the time period beginning in January 2011 to January 2012 for U.S. domestic flights.

Referencing table 1 and figure 1, an air carrier delay is one considered within the control of the airline, such as a baggage-related delay or a crew arriving late from another flight. A delay attributed to the National Airspace System (NAS) may be caused by a
wide range of reasons from less-than-extreme weather conditions to airport or airspace congestion issues. A weather delay refers to extreme weather, such as a blizzard, hurricane, or tornado. Figure 2 displays the recorded percentages of total U.S. airline delays for domestic flights over the time period beginning in 2003 through 2010, and reiterates that the air carriers, themselves, have the greatest impact on their own, perceived, on-time performance.

<table>
<thead>
<tr>
<th></th>
<th>Number of Operations</th>
<th>% of Total Operations</th>
<th>Delayed Minutes</th>
<th>% of Total Delayed Minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>On Time</strong></td>
<td>5,252,149</td>
<td>79.92%</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Air Carrier Delay</strong></td>
<td>333,048</td>
<td>5.07%</td>
<td>19,744,970</td>
<td>30.13%</td>
</tr>
<tr>
<td><strong>Weather Delay</strong></td>
<td>33,621</td>
<td>0.51%</td>
<td>2,773,830</td>
<td>4.23%</td>
</tr>
<tr>
<td><strong>National Aviation System Delay</strong></td>
<td>377,108</td>
<td>5.74%</td>
<td>16,287,623</td>
<td>24.86%</td>
</tr>
<tr>
<td><strong>Security Delay</strong></td>
<td>2,436</td>
<td>0.04%</td>
<td>85,059</td>
<td>0.13%</td>
</tr>
<tr>
<td><strong>Aircraft Arriving Late</strong></td>
<td>434,568</td>
<td>6.61%</td>
<td>26,634,885</td>
<td>40.65%</td>
</tr>
<tr>
<td><strong>Cancelled</strong></td>
<td>123,082</td>
<td>1.87%</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Diverted</strong></td>
<td>15,403</td>
<td>0.23%</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Total Operations</strong></td>
<td>6,571,414</td>
<td>100.00%</td>
<td>65,526,367</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

- When multiple causes are assigned to one delayed flight, each cause is prorated based on delayed minutes it is responsible for. The displayed numbers are rounded and may not add up to the total.

Table 1: On-Time Arrival Performance, National (January, 2011 - January, 2012) (BTS, 2012)
Figure 1: On-Time Arrival Performance, National (January, 2011 - January, 2012) (BTS, 2012)

U.S. Air Carrier On-Time Performance
January 2011 to January 2012

- On Time: 79.92%
- Air Carrier Delay: 5.07%
- Weather Delay: 0.51%
- National Aviation System Delay: 5.74%
- Security Delay: 0.04%
- Aircraft Arriving Late: 6.61%

Figure 2: U.S. Airline Flight Delay Causes by Year (BTS, 2012a)
Flight departure delays may result in propagated “late” arrivals throughout a day of airline operations, but block times may not reflect propagated delays as they only include the elapsed time from gate to gate. Unexpected delays occurring after an aircraft leaves the airport departure gate, such as when taxi times increase due to congestion, or occurring prior to parking at the destination airport gate, such as when an aircraft must hold in flight prior to landing, are, however, components of that flight’s block time. A subsequent flight using the same aircraft as a late-arriving flight may depart the gate after its scheduled departure time, but could arrive at its destination in less elapsed time than the predicted block time for that flight segment. This flight may still arrive 15 minutes or more after the published arrival time, and, therefore, is recorded as late. Airlines must balance more accurate block time predictions with current, very publicized, on-time performance demands.

1.4 Block Times and Fleet Type

If an airline’s total fleet of aircraft consists of more than one type, block times will vary with the performance capability of each type of aircraft assigned to specific city pairs. An aircraft type is defined by the Federal Aviation Administration (FAA) as follows. “As used with respect to the certification, ratings, privileges, and limitations of airmen, type means a specific make and basic model of aircraft, including modifications thereto that do not change its handling or flight characteristics,” and “as used with respect to the certification of aircraft, type means those aircraft which are similar in design,” (FAA, 2012, FAR Part 1.1).
The type or types of aircraft selected by an airline for its network of operations, depend on the desired network and route structure of that airline, as well as anticipated demand for service between city pairs. Aircraft types of similar size and capacity will typically have similar performance capabilities, and, thus, similar block times between city pairs. Conversely, aircraft types differing greatly in size and capacity may have very different performance capabilities. For airlines operating more than one type of aircraft, block time prediction depends, in part, on which aircraft type is assigned to fly on each route.

1.5 Block Time Prediction and Historic Data

To maximize profits, or to simply generate any profit, airlines endeavor, like all businesses, to maximize revenues and minimize costs. A measure of revenues obtained through the sale of passenger tickets is yield. Yield is defined as the amount the average passenger in an airline’s network pays to fly one mile, and is currently approximately 14 cents per mile for U.S. airlines flying domestic routes (BTS, 2011). Creating fare structures that maximize an airline’s yield is the focus of many academic investigations using stochastic modeling techniques. Mahnke et al explain that “one of the main problems in the theory of stochastic processes is to find mathematical models that describe the evolution of a system in time and especially be used to predict, not without error, the values in the future with the help of information collected about the process collected from the past,” (Mahnke, 2009, 7). This describes the intent of airline block time prediction modeling, precisely. Airlines rely on historical data to predict future
block times, but an airline’s network evolves dynamically through the adding or subtracting of service to existing or new city pairs, and is affected by the many components and environments interacting with the network.

An airline determines and controls the number of flights available between city pairs, as well as the fare structure and availability of the seats on each flight, but must predict the passenger demand. The anticipated demand, in turn, not only affects the fare structure, but determines the assignment of aircraft type to a set of flights on any particular day. Each passenger contributes differently to an airline’s network, and an itinerary may have an origin and destination (O&D) requiring one flight leg or many legs to complete a single trip. Maximizing yield and, therefore, revenue, is dependent on the ability to model and predict at the network level as well as at the individual flight level. This must all occur within FAA regulatory constraints and, often, while adhering to union rules and contract stipulations.

1.6 Direct Routing, Block Time, and the FAA’s NextGen Program,

From an airline operations viewpoint, the goal of any individual flight segment is, of course, to fly as direct a route as possible (great circle distance) between airports. For a variety of reasons, this direct routing is not often a possibility. Reliance on ground-based navigation facilities and equipment and air traffic control (ATC) are currently the most limiting factors, although air traffic controllers also desire the most expeditious means of routing each flight. Regardless of the desired and requested routing between city pairs for each flight segment, ultimately it is ATC granting the clearance and
dictating the actual route of flight. Other significant factors preventing direct routing include active military airspace, congestion, and weather.

Although there are many factors that could prevent or allow direct routing on any flight segment, they are not entirely random. The average, historic block time between a city pair will reflect the typical routing between those, two airports, and also show the resulting deviations from that typical block time. The factors preventing or allowing direct routing are embedded in these historical performance data, and surround the typical block times and routing for the chosen time period. When the distribution of the actual block times for a chosen time period and city pair is plotted, the range of routing and times experienced for that city pair is evident. To alter this distribution in the future, a means of affecting the routing on each flight segment on a consistent basis is required. The FAA’s Next Generation Air Traffic (NextGen) system aims to accomplish this through implementing the technology to allow user-defined, direct routing more often while maintaining the safe separation of aircraft. This NextGen system is a transformation of the air traffic control system in the United States consisting of multiple programs collectively aimed at reducing overall passenger travel time and increasing air transportation efficiency (FAA, 2011).

The six, “nucleus” FAA NexGen programs include creating a “satellite-based successor to radar,” (FAA, 2011, slide 4) and updating the air traffic control system with more efficient means of communications between ATC facilities, as well as between ATC and pilots. Enhancing air traffic flow is both an overall objective and an individual program forming the core of the NextGen system, and performance-based navigation is considered integral to its success. Required Navigation Performance (RNP) is a
descriptive term encompassing and quantifying the concept of performance-based navigation in airspace and with respect to navigation procedures and accuracy.

“Required Navigation Performance (RNP) takes advantage of new onboard technologies for precision guidance to help transition the U.S. National Airspace System (NAS) from reliance on airways running over ground-based navigation aids to a point-to-point navigation concept,” (FAA, 2011). Area Navigation (RNAV), the foundation of RNP, uses ground-based navigation facilities and equipment, GPS, and navigation capabilities internal to an aircraft, either individually or in combination, to create a user-defined path of flight. RNAV facilitates point-to-point routing, and, therefore direct routing. When aircraft navigation performance monitoring and alerting also comprises an aircraft’s navigation capabilities, RNAV becomes RNP.

Figure 3: Performance-Based Navigation: RNAV/RNP (Day, 2009)
1.7 RNP

RNP refers to a navigation performance level required for operations within specific, defined airspace. The RNP value is expressed in nautical miles, and refers to the maximum distance allowed between the actual position of the aircraft and the value calculated as the actual position by the aircraft’s onboard systems. The actual aircraft position calculated by onboard aircraft systems has an associated probability level of its accuracy. This confidence level is a percentage value that the aircraft is located within a circular radius distance of the calculated position, and is required to be 95 percent or greater for RNP-designated airspace. This precision capability and probability level is what allows for there to be less separation distance between aircraft and from terrain compared with traditional air navigation using ground-based aids alone. The International Civil Aviation Organization (ICAO) definition of RNP is “a statement of the navigation performance accuracy necessary for operation within a defined airspace,” (ICAO, 2008). Simply summarized, RNP removes dependence on ground-based navigation aids.

The RNP level is very large, as large as 10 nautical miles, in uncongested airspace, such as in high altitude, oceanic airspace. Conversely, congested airspace, such as the airspace surrounding the busiest airports, requires very small RNP values to ensure safe separation of aircraft. There is a much greater need for increased accuracy with respect to aircraft position when close to terminal areas (airports) than in the cruise flight phase, and the RNP value may be as low as 0.1 nautical mile for instrument approach procedures. All flight procedures based on RNP include a designated, required performance level, and, therefore, RNP is both a measurement of navigation performance
accuracy and a requirement. The actual navigation performance (ANP) of an aircraft calculated by its internal flight management computer (FMC) must be better than the designated RNP to use RNP procedures.

The International Civil Aviation Organization (ICAO) terminology for RNP instrument procedures approved for use at individual airports is RNP/AR (ICAO, 2008). AR represents “Authorization Required.” An airline must be granted the approval to conduct RNP instrument procedures by their country’s civil aviation authority, and, as part of that authorization, the flight crews must individually complete training on RNP navigation and procedures. RNP/AR instrument approach procedures utilize the increased navigation accuracy of capable and authorized aircraft to safely allow increased use of parallel or converging runways. This increased navigation and present position accuracy increases airport terminal airspace capacity and efficiency while simultaneously reducing ATC workload and needed verbal instructions and confirmations. Currently, the availability of RNP/AR procedures is increasing for arrivals to and departures from U.S. airports, for those airlines authorized to use them, allowing for increased traffic flow at those airports. As more airlines are authorized to use published RNP/AR procedures, the rate of individual airport operations (takeoffs and landings) able to be processed will increase. This increased capacity will likely decrease congestion at these airports, unless the number of demanded operations increases at the same or a greater rate. When all airlines and all large airports are able to utilize RNP/AR procedures, significant increases in efficiency and reduced congestion-related delays will be realized. Block times to and from these airports will decrease, and the variation in block times caused by airport operations-related congestion will also decrease as a result.
To use in conjunction with RNP/AR procedures, the FAA is implementing Automatic Dependent Surveillance Broadcast (ADS-B), which will replace traditional surveillance radar with Global Navigation Satellite System (GNSS) technology to provide aircraft position information to air traffic controllers and to other aircraft (ADS-B Technologies, 2011). Increased precision with respect to aircraft position reporting will enable ATC to allow reduced aircraft separation distances without compromising safety. When used in conjunction with RNP/AR procedures, an increased capacity of flights in and around terminal areas will result while safe aircraft separation is maintained. Delays resulting from congestion in the airspace around and between airports will be reduced, and the actual block times experienced between city pairs will decrease and stabilize.

1.8 RVSM

Air traffic control must facilitate and maintain the lateral and vertical separation of flights operating on instrument flight plans. An instrument flight plan is required when the weather conditions, meaning visibility and location and coverage of clouds, is below those established by the FAA as minimum for piloting a flight solely by outside visual references. The FAA’s Visual Flight Rules (VFR) apply to flights operating in weather conditions at or above these establish minima, referred to as operating in visual meteorological conditions (VMC). The Instrument Flight Rules (IFR) apply to flights operating in less than VMC. An instrument flight plan is also required to operate an aircraft above 18,000 feet mean sea level in the U.S., regardless of the weather conditions.
Air traffic control assigns routes and flight altitudes for all flights on instrument flight plans with the objective of safe separation between aircraft. Minimizing the separation distance needed between aircraft, both laterally and vertically, without compromising safety increases the capacity of the airspace. “The FAA has implemented the use of Reduced Vertical Separation Minima (RVSM), which reduced the minimum vertical separation between aircraft from 2,000 feet to 1,000 feet for all properly equipped aircraft flying between 29,000 feet and 41,000 feet. This increased the number of routes and altitudes available, and allows more efficient routings,” (FAA, 2011, Brief History). Like with RNP, the benefits of RVSM will increase as more aircraft are equipped with the updated technology.

NextGen commenced in 2004 and continues to evolve. Figure 4 provides the FAA’s estimated costs versus benefits comparison for the NextGen program through 2012. Until the FAA fully implements their NextGen system, though, direct routing cannot be guaranteed, and may not be possible on many flight segments, (FAA, 2011, NextGen). A new prediction method for block times cannot reduce the variation of the actual times experienced, but the implementation of the NextGen system to allow for direct routing on a consistent basis will allow this to occur. As direct routing becomes possible and is used throughout the National Airspace System, the standard deviation of the distribution of the actual block times for each city pair will decrease and stabilize.
Figure 4: Projected FAA NextGen Program Costs vs. Benefits (ATA, 2009)
CHAPTER 2: COMPUTATIONAL FRAMEWORK

Airline historic data typically is the foundation of block time prediction models, and stochastic modeling of various components of airline operations has been, and continues to be, the focus of many academic researchers. “A stochastic model is a tool for estimating probability distributions of potential outcomes by allowing for random variation in one or more inputs over time,” (Class of 1, 2011). Stochastic projections (simulations) have been used in academic research to predict distributions of potential outcomes “which reflect the random variation in the input,” (Class of 1, 2011), but with respect to airline operations, the historic data provides baseline probability distributions. Although the variation in the distributions of historic airline performance data represents the fluctuations experienced, these fluctuations are not completely random.

2.1 Block Times and Crew Scheduling

As previously stated, airlines develop a master flight schedule of service between city pairs incorporating aircraft scheduled maintenance requirements, then create a schedule of flight sequences, made up of combinations of flight segments (or legs) for pilots and flight attendants. The objective is to optimize the utilization of the crews and the aircraft on a daily basis while adhering to all maintenance-related, regulatory, and labor contract constraints. Optimization of crew schedules requires the minimization of
hotel stays, deadhead flights (where the pilot must fly as a passenger to reach the starting point of an assigned trip), and waiting times between flights (sits), while simultaneously maximizing crew and aircraft utilization.

A flight crew and cabin crew (pilots and flight attendants) must be assigned to each flight segment in the master airline schedule, and these crew members may be based at one of many cities within the U.S. A base is an assigned airport from where a crew member is considered to be located as their primary starting point (home base) for scheduled trips. A pairing is the assignment of crew members to a sequence of flight segments that begin and end at a specific crew base. As master schedule disruptions are exacerbated when pilot crews are separated during a daily sequence of flights, pilot crew members are paired together for the duration of a flight sequence whenever possible. This also improves crew resource management on the flight deck, and, therefore, increases safety (Helmreich et al, 1999). Additionally, assigning a pilot crew to a single aircraft for as many flight segments as possible in a sequence of flights has been shown to increase operational dependability and optimization (Anbil, 1991, 64).

Crew pairing optimization within the master schedule has been the subject of ongoing research since the 1950s, because small improvements translate into very large savings for an airline (Anbil, 1991, 63). Anbil et al reported that “a one percent increase in American Airlines’ crew utilization translates into a $13 million savings (in 1990 dollars) each year,” (Anbil, 1991, 63). Although flight crews are paid by the block hour, usually with a guaranteed minimum number of hours per month, additional pay is provided when a crew member must remain overnight at a location other than his home base, or if the crew member must deadhead to an airport from his home base to begin a
flight sequence. Accurate block times are relied upon as data from which crew pairings are developed. Understanding the complexity of crew qualifications and scheduling limitations provides a foundation to understand the relationship to block times, as well as associated operations challenges.

Pilots must be type rated by the FAA to act as pilot in command of any aircraft in the U.S. which meets any of the following criteria designated by FAR Part 61 (FAA, 2012).

1. An aircraft with a maximum certificated takeoff weight greater than 12,500 pounds.
2. An aircraft powered by turbojet engines.
3. Any aircraft specified by the FAA Administrator as requiring a type rating to operate as pilot in command.

Pilot in command is defined by the FAA as the person who:

1. “has final authority and responsibility for the operation and safety of flight,”
2. “has been designated as the pilot in command before or during the flight, and”
3. “holds the appropriate category, class, and type rating, if appropriate, for the conduct of the flight.” (FAA, 2012, FAR Part 1.1)

Scheduled air carriers (airlines) operating within the United States are certificated to operate under FAR Part 121, and must adhere to this set of regulations. With respect to crew scheduling, an airline may only assign pilots to fly aircraft for which they are type rated, and, additionally, on-going training (every six months) is required for a pilot to remain current and legal to fly the aircraft for which they hold a type rating. Pilots are
highly trained, they must work within a strict regulatory framework, and they represent the highest labor costs for an airline. The optimization of crew scheduling for large airlines is a substantial integrated systems problem, and one which depends on accurate block time predictions as an integral component of their models.

Johnson (2005) uses surrogate models for the sub-problems of crew scheduling, aircraft maintenance scheduling, and revenue generation, then combines the sub-problem solutions into a single, decomposable model prior to solving for an optimal solution. Johnson’s objective is to treat airline schedule planning in an integrated manner to obtain a “global optimum” solution. The excerpt below from this work indicates that block times are assumed to be known data with their accuracy depended upon to validate the surrogate models and for their successive use to generate a global, optimum schedule (Johnson, 2005, 42-44).

Master Schedule Objective Function:

$$\min \sum_{(nm) \in A} c_{i(n)j(m)}x_{ij} + \sum_{b \in B} f_b(x)$$

Johnson states that “this objective function minimizes the fuel costs of the schedule plus the sub-problem cost contributions” (Johnson, 2005, 44), and the summary of notation follows.
Sets:

$\mathbf{I}$ Airport indices

$\mathbf{T}$ Discrete time increment indices

$\mathbf{N}$ Location-time nodes, where $\mathbf{N} \subset \mathbf{T} \times \mathbf{I}$

$\mathbf{N}(t)$ Nodes that correspond to time $t$

$\mathbf{A}$ Arcs, where $\mathbf{A} \subset \mathbf{N} \times \mathbf{N}$

$\mathbf{A}(t)$ Arcs that are active at time $t$, i.e. $\tau(n) < t$ and $\tau(m) > t$ for $(nm) \in \mathbf{A}(t)$

$\mathbf{A}^\varphi$ Flight arcs, where $\tau(m) - \tau(n) = t$ and $i(n) \neq i(m)$ for $(nm) \in \mathbf{A}^\varphi \subset \mathbf{A}$

$\mathbf{A}^\vartheta$ Ground arcs, where $\tau(m) - \tau(n) = 1$ and $i(n) = i(m)$ for $(nm) \in \mathbf{A}^\vartheta \subset \mathbf{A}$

$\mathbf{B}$ Subproblem indices

Data:

$t_{\text{max}}$ Index of final increment

$c$ Cycle time, or length of one day

$t_{ij}$ Travel time from location $i$ to location $j$ (block time)

$c_{ij}$ Fuel cost for travel from $i$ to $j$

$\gamma(i)$ Minimum turn time at location $i$
$r_i^+, r_i^-$ Maximum takeoff and landing rates at location $i$

$g_i$ Ground capacity at location $i$

$V$ Number of airplanes available in the system

$i(n)$ Location of node $n \in N$

$r(n)$ Time of node $n \in N$

Decision Variables:

$x_{nm}$ Flow (i.e. number of aircraft scheduled) on arc $(nm) \in A$

Johnson continues by developing the surrogate models for aircraft maintenance scheduling, crew scheduling, and revenue generation. Both the crew scheduling and revenue generation models require block times as known, accurate data.

Schaefer and Nemhauser focus on “keeping a schedule legal while not increasing the planned cost of the crew schedule” through “perturbing scheduled departure and arrival times after a crew schedule has been found.” (2002, abstract). Their work relies on having accurate block times as given, accurate data, as described below.

Schaefer and Nemhauser reiterate that, traditionally, an airline first determines where and when it will fly, then, if an airline operates multiple aircraft types, assigns a type of aircraft to each flight segment. Next block times are determined, maintenance considerations are added, which results in aircraft routings, and then finally, crew pairings are developed to match the master schedule. These authors determined the planned duty cost of a crew schedule as:

$$b(d) = \max \left\{ \sum_{i \in d} \text{block}(i), r_e \times \text{elapse}(d), mg_d \right\}$$
where the planned block time of leg \( l_i \) (in minutes) is \( \text{block}(l_i) \). From here, a planned flight-time-credit, designated FTC, is calculated as follows, and where \( \text{block}(C) \) is the total scheduled block time of all legs in the flight schedule.

\[
FTC(C) = \left[ \left( \frac{c(C) - \text{block}(C)}{\text{block}(C)} \right) \times 100 \right]
\]

In Schaefer and Nemhauser’s work, the goal is to take a master schedule already developed with the crew scheduling completed, then to perturb or “tweek” the predicted and scheduled block times without increasing crew costs to increase operational efficiency. Constraints are applied to prevent an increasing or decreasing planned block time from violating crew-related constraints or from making passenger itineraries infeasible. The predicted and scheduled block times are assumed to be given data with the intent being to adjust these block times without increasing crew costs or negatively affecting passenger connections (Schaefer and Nemhauser, 2002).

2.2 Predicting Components of Block Time

Balakrishna et al (2008) break down the problem of predicting accurate block times into the components contributing to the total block time, then focus only upon the taxi time component. They stress that the difficulty in predicting taxi times, especially at congested airports, not only negatively affects the overall difficulty in estimating block times, but has added implications with respect to jet engine emissions and noise concerns while an aircraft is on the ground (Balakrishna, 2008).
Taxi-out time and taxi-in time are specific components of block time. The taxi-out time begins when the aircraft is pushed back from the departure airport gate, and ends when the aircraft departs the runway (gear up) on takeoff. The taxi-in time begins after the aircraft touches down upon landing, and ends when the aircraft is parked at the arrival airport gate. Taxi times at very congested airports are difficult to predict, and may have a large impact on the overall block time.

Balakrishna et al focus on the block time component of taxi-out time alone, and use a “model free non-parametric Reinforcement Learning (RL) algorithm” to estimate taxi-out times “at least 15 minutes” prior to scheduled aircraft pushback from the departure gate (Balakrishna, 2008, 3.D.3-2). These researchers use average, historical, taxi times as part of defining the system state that also includes the number of aircraft taxiing for departure, the number of aircraft taxiing after landing, and the time of day.

Balakrishna et al also contend that dynamically adjusting an actual departure time will minimize airport congestion (Balakrishna, 2008, 3.D.3-2). Block times are estimated months prior to the actual operations, and gate assignments, passenger connections, crew scheduling, etc. are all predicated on these determinations. An early departure with respect to the scheduled departure time is not possible without significant notice to the passengers, and holding an aircraft at its departure gate could prevent the next, scheduled, arriving flight from parking at that gate. Dynamically adjusting the scheduled time for the pushback of an aircraft from its gate, as an ATC function, could help alleviate the number of aircraft in line for takeoff during specific time intervals, but the negative impact of increasing the number of aircraft waiting for an open gate (increased ramp congestion and fuel burn) and increasing the number of statistically late departures are
both significant and expensive operational considerations. From an airline perspective, identifying a probable, increased, taxi time at a specific airport close to the scheduled departure time may allow for disruption mitigation strategies to be implemented more quickly and is valuable data with respect to tracking average taxi times at specific airports, but a published, scheduled departure time cannot be altered without significant, advanced notice to all passengers.

Balakrishna et al provide background information on the positive effects on taxi times of airports implementing optimized taxi routing and runway assignments (2008). Airport flow rates may be controlled and congestion minimized through air traffic control (ATC) procedures, takeoff and landing reservation programs, and optimization models aimed at taxi route efficiency. These programs are ATC-based, and their optimization models use the published, scheduled airline arrival and departure times generated using block time predictions, as part of their efforts to minimize taxi times. Airlines typically incorporate average, historic block times into their methodology to predict these future block times for their network’s specific city pairs.

Aron Futer published findings related to improving the FAA’s Enhanced Traffic Management System (ETMS), which has the objective of improving the efficiency of air traffic control in the United States (Futer, 2007). He states that taxi times, in turn, have four components: “seasonal trend, day of the week effect, daily propagation pattern, and random error,” and that narrowing the distribution of the ground delay times was a goal of that research (Futer, 2007, 2E1-2). Like Balakrishna et al, the objective of ETMS is to predict and accommodate traffic flow at airports the day of departure, not with advance planning.
2.3 Block Time Prediction Modeling and Delay Propagation

Arikan et al (2010) focus on intrinsic versus propagated aircraft delays using scheduled and actual block times, but incorrectly utilize block time in their model. Their objective is to “construct a probabilistic model of total block time instead of breaking it up into segments,” (Arikan et al, 2010, 4), but claim that a departure delay is one of the segments comprising total block time. These researchers relate the block times to the scheduled times of departure and arrival rather than elapsed time, although they mathematically define total block time correctly as flight arrival time at the gate minus flight departure time from the gate. Any block time may be affected by aircraft delays propagated during a day of operations, but that effect is due to increased congestion, both on the ground and in flight. A flight leaving late may have the exact block time between a specific city pair as a flight leaving on time. Departure and arrival delays are typically propagated through a day, but this does not, automatically, increase the block times of subsequent flight segments. Although Arikan et al claim to build on a model developed previously by Deshpande and Arikan (2009), which “follows a log-Laplace distribution,” (2010, 10), no publication could be found for this reference. Arikan et al also discuss the “variance in block times across all flights”, and describe these variances as “heteroscedastic,” (2010, 12). This described variability in the subsets of chosen, actual, block time distributions for specific city pairs is a focus of the current research.

Sohoni et al (2008) titled their published work “Block Time Estimation and Robust Airline Scheduling,” but endeavor to maximize airline profits through the optimization of airline schedule planning. They state that they developed “a model that perturbs a proposed flight schedule by considering block time distributions,” (Sohoni et
They also state that their work is “an initial attempt at developing a comprehensive and holistic model for block time estimation,” (Sohoni et al, 2008, 4). The first model presented in their publication focuses on maximizing operational profits, and uses net revenue and a departure delay penalty in the objective function. Passenger itinerary considerations and on-time performance restrictions are embedded in the constraints. This model assumes an extremely high level and basic view of airline operations and profits without considering the complications associated with the dynamic and complex nature of passenger demand and fare classes.

Presented as an “alternate goal,” Sohoni et al present a second model aimed at maximizing a defined airline on-time performance service level across an entire network, and use their previously described objective function as a constraint. They define the service level pertaining to the BTS-tracked, on-time performance statistics as excerpted below, and state that block time is the only random variable in their model. “The FSL is the probability that a particular flight is not delayed based on the Department of Transportation acceptable arrival delay measure $\delta$, (Sohoni et al, 2008, 8).”

$$FSL_i = \Pr[Y_{i, \text{di}} \leq a_i - d_i + \delta]$$

$Y_{i, \text{di}} =$ block time of flight $i$ with departure at time $d$

$a_i =$ arrival time of flight $i$

$d_i =$ departure time of flight $i$

$\delta =$ DOT-defined on-time performance measure ($< 15$ minutes)
Sonhoni et al assume that “block time distributions are log-concave and stationary with respect to the departure time,” (2008, 11). Although the probability distributions may be assumed to be log-concave, the distributions of the actual, historic block times are not. These researchers did not develop a model to more accurately predict block times, but, instead, created models with the intention of varying scheduled departure times to attempt to maximize their definitions of service and operational reliability.

2.4 Historic Block Time Distributions and Delays

According to Lada A. Adamic, an associate professor at the University of Michigan, the terms Pareto and power law are both used to describe a system where there are many, common smaller events, but few large events, (Adamic, 2002). With respect to airline operations, small delays or early arrivals with respect to the exact, predicted arrival or departure times are very common, but the very large delays or very early arrivals are not frequent.

Pareto’s Law could be explained by saying that it focuses on the number of airline flights that are early or delayed, as opposed to the size of the difference between the actual and predicted flight arrival and departure times.

\[ P[X > x] \sim x^{-k} \]  

(Pareto’s Law CDF)

Dr. Adamic explains that “Pareto’s Law, above, is given in terms of the cumulative distribution function (CDF), i.e. the number of events larger than x is an inverse power of x.” Applied to the number of flight times that differ from the scheduled departure or
arrival times, Pareto’s Law says that the number of times a flight is early or late that is greater than $x$ times is an inverse power of $x$.

A power law distribution is described by Dr. Adamic as “the probability density function associated with the CDF given by Pareto’s Law,” and she explains that it describes the number of times $x$ is exactly a specific value. In the context of flight delays, it would describe the number of flights with a delay or early arrival of exactly $x$.

\[ P[X = x] \sim x^{-(k+1)} = x^{-a} \]  

(Power Law Distribution)

For data distribution with extreme distributions (“L” shaped), the Pareto cumulative distribution provides a better fit of the more infrequent data values within the tail portions of a power law distribution than a log-log plot, (Adamic, 2002).

Michael Mitzenmacher, Professor of Computer Science at Harvard University, discusses the finite mean and variance as properties of a lognormal distribution, as well as the similarities to power law distributions. Dr. Mitzenmacher makes the point that large systems converge to a double Pareto distribution, which is when power law behavior is exhibited in both the upper and lower tails of the distribution, (Mitzenmacher, 2003).

A log-Laplace distribution is given by the probability density function below, and has “a distinct tent shape,” (Kozubowki and Podgórska, 2003, 3).
\[ g(x) = \begin{cases} \frac{1}{\delta} \left( \frac{\alpha \beta}{\alpha + \beta} \right) x^{\beta - 1} & \text{for } 0 < x < \delta \\ \left( \frac{\delta}{x} \right)^{\alpha + 1} & \text{for } x \geq \delta \end{cases} \]

As mentioned previously, Arikan et al claim that block time of a flight follows a log-Laplace distribution, (Arikan, 2010, 10). When the logarithm of the distribution of a random variable is normally distributed, it is referred to as a lognormal distribution, and is described as follows along with the associated probability density function (Mitzenmacher, 2003).

\[ Y = \ln X \quad \text{(Lognormal Distribution)} \]

\[ f(x) = \frac{1}{\sqrt{2\pi \alpha}} e^{-\left(\ln x - \mu\right)^2 / 2\sigma^2} \quad \text{(Lognormal Distribution PDF)} \]

Andrew Schaefer (2000) describes the difference between predicted block time and actual block time as a random block error, and uses the equation below within his airline crew scheduling simulation.

\[ arr(l) = block(l) + dep(l) + \omega_l \]

Actual departure time of flight leg \( l \) is represented by \( dep(l) \) and actual arrival time of leg \( 1 \) by \( arr(l) \). \( block(l) \) is the scheduled block time of leg \( l \) with \( \omega_l \) representing Schaefer’s described random block error. Although Dr. Schaefer proposes varying scheduled block times to improve overall operational performance after an initial crew schedule has been
created, his research does not address the quality of the predicted, scheduled block times or the minimization of the difference between scheduled and actual block times.

Researcher Rosenberger, in conjunction with Schaefer, continued their airline operations simulation, and published additional findings in 2002. They use a “discrete event, semi-Markov process” for their stochastic model of airline operations (Rosenberger et al, 2002, 361), and focus on crew scheduling and crew schedule recovery after a disruption. The actual block times for their simulation were generated using historic block times plus a random block error, as was described with respect to the equation provided by Schaefer.

2.5 Block Time Estimation

In 2006, Steven Coy of the University of Houston published a model to estimate the future block times of domestic, commercial airline flights in the U.S. (Coy, 2006). His model combines a historic average of actual block times for each, specific city pair with a linear set of added variables and coefficients. Many of the variables are binary. Mr. Coy writes that a major source of variation in actual block times is the “queuing” of arrival and departure flights, meaning the line-up of flights waiting their turn to land or takeoff. He states that weather affects these lines by reducing the airport service rate while the arrival/departure rates remain as scheduled or greater.

Mr. Coy cites Citrenbaum and Juliano’s research (1999) as showing 60% to 70% of all flight delays greater than 15 minutes in the U.S, are caused by weather. He says that, coupled with peak arrival and departure periods of time at large, commercial
airports, the variability of actual block times is at its greatest during periods of poor weather, but his variables are too specific to be used on the broad scale needed for airline schedule development. For example, his variables \( TS, I_0, \) and \( I_d \) attempt to sum the impact of thunderstorms and icing conditions for the origin airport, enroute, and at the destination airport. While these impacts are real and relevant, they simply cannot be accurately predicted, much less quantified, six months or more in advance. Mr. Coy’s other variables include flight arrival time of day, airport utilization factors, and the population of the areas surrounding the airports.

2.6 Block Time Prediction Factors and Foundation

The estimation of the block times for commercial, domestic, airline operations requires a probabilistic, general model that can be easily customized and updated for a specific airline’s network. As individual block times vary by season, by day, and by time of day, the challenge is to make general, long-term estimations that represent the average, actual block times with minimal variation. With respect to the newly developed block time prediction model, the following factors are addressed.

- Peak hours of operation for the departure and arrival airports (congestion)
- Seasonal weather (likelihood of delays and/or disruptions)
- Seasonal routes
- Route region
- Short haul or long haul flight
- Previous years’ block times
- RNP capabilities/procedures

Airline on-time performance data, available from the Bureau of Transportation Statistics (BTS) via their website, was downloaded and filtered to comprise of only Southwest Airlines data. Southwest Airlines operates only Boeing 737 type aircraft, with thousands of domestic flights per day. Their operation provides a very large quantity of information from flights with consistent aircraft performance capabilities.

The planned block times published by BTS for any, specific airline reflect that airline’s current method of block time estimation. Southwest Airlines operates well over 3000 domestic flights per day using over 500 aircraft, and currently utilizes a computer program developed internally to predict block times between each city pair for which they provide service. The program receives direction from the program user to reference linked, in-house data from one, or more, time periods chosen by the user. Southwest Airlines schedules flights in seasonal time periods, and uses the actual block times from the matching time periods from chosen, previous operations to estimate probable block times for flights during the same, future time period. The average length of actual block time is one criterion the computer program uses to select and retrieve historical data, and this length is chosen/input by the program user. For the new model and for Southwest Airlines’ previous predictions, less than a 91 minute block time is designated as “short-haul,” and greater than 90 minutes as “long-haul.” A separate, estimated set of block times is determined using the new model for the short- and long-haul sets, and is also used for comparison purposes.
The internal user of Southwest Airlines’ current, block time prediction, computer program chooses and inputs a statistical percentile for which a corresponding set of block times will be output. For short-haul flights, Southwest Airlines uses a selected, specific percentile block time (the number of minutes that encompasses that percentage of all the historic, actual block times for a specific flight/city pair and the time periods chosen), and does the same for long-haul flights.

The output from this program includes actual block times for the flights previously flown during the selected time period. To retrieve these times, the program references the flights for the planned, future time period, then finds the single flight in the historic data that most closely matches the departure time of the future flights. If an exact match is not found, the program searches the historic data in smaller increments until it finds the flight closest in departure time to the planned flight between the same city pair. The program also provides a set of block times that are the actual block times rounded per programmed criteria. The block times corresponding to each, statistical percentile value in the referenced distributions of actual block times, beginning at a specific percentage value, are output as well. As the scheduled block time for each city pair incorporates the historic actual block times for the matching city pair, it provides a powerful, independent variable on which to base a more general, and more accurate, prediction model.
2.7 Linear Relationship Validation and New Model Development

Prior to developing the new block time prediction model, and using the Southwest Airlines published, historic data, the linear relationship between predicted and actual block times for all city pairs in their network was validated. This was accomplished by sorting and separating the Southwest Airlines performance data for various time periods from 2005 through 2011. The sorted data was separated by day of the week for a single month, and averages were obtained for the departure delays and arrival delays associated with each city pair departing at differing times during each day. A general, linear regression equation was obtained for each day of the week for each, separate, single month. All generated linear regression equations match consistently, without exception, indicating that the individual factors affecting each flight vary by season, by month, by day of the week, and by time of day.

The historic data, when partitioned by month, day of the week, and by scheduled departure time, reflect the actual block times between city pairs, plus or minus any delays actually experienced after leaving the departure gate and arriving at the destination airport gate. These delays may have occurred due to airport or airspace congestion, weather, or operational issues, and may also reflect early arrivals or departures via negative values.

While these individual causes of delays are too specific to accurately predict in advance for an extended time period (six months or more in advance), they can be incorporated in a general manner into a model based on more specific, historic data,
resulting in a reduction in the variance of the differences between scheduled (predicted) block times and actual block times.

To create a new block time prediction model, on-time performance data for all flights occurring in July, August, and September of 2010 from the U.S. Department of Transportation (DOT), Bureau of Transportation Statistics (BTS), Research and Innovative Technology Administration (RITA) website (BTS, 2011) were downloaded, and then sorted for Southwest Airline flights, only. These data were further partitioned by individual flight segment and day of the week. For each day of the week within the targeted three month period, the flights were chronologically ordered by their scheduled departure time, then also alphabetically sorted by city pair within the scheduled departure time. Using a database software query function, tables were created to combine the third quarter, 2010, Southwest Airlines sorted data.

Additional sorting was accomplished to further identify and separate these data by long and short haul flight durations, then sorted further to create individual tables containing these Southwest flights for each day of the week and scheduled time of departure, all chronologically ordered. Each day of the week was divided into three flight departure time periods (24-hour time scale):

- Scheduled Departures Prior to 1000
- Scheduled Departures After 0955 and Before 2000
- Scheduled Departures After 1955

These time partitions were selected to capture effect the increased congestion accompanying the early morning and early evening departures associated with business
travel. The resulting database includes a table of original BTS data, and all subsequent tables resulting from the partitioning and sorting of that original, raw data. For the third quarter of 2010, these resulting tables contain data sorted for:

- Airline (Southwest Airlines)
- Season (third quarter, 2010)
- Long-Haul and Short-Haul Flights (> 90 minutes and < 91 minutes)
- Day of the Week
- Scheduled Departure Time of Day
- City Pair (Flight Leg Origin and Destination)

The third quarter data for 2010 resulted in well over 100 queries and tables to adequately filter the BTS data. Using this combined and sorted data for the third quarter months of July, August, and September of 2010, an average block time value was calculated for each city pair, and the following general, linear regression equation was validated.

\[
\text{Average Actual Block Time} = \beta_0 + \beta_1 \text{SWA} - \text{ADD} + \text{AAD} + \epsilon
\]

\( \text{SWA} \) = Southwest Airlines Average Predicted Block Time

\( \text{ADD} \) = Average Actual Departure Delay

\( \text{AAD} \) = Average Actual Arrival Delay

\( \beta_0 \) = Regression Coefficient

\( \beta_1 \) = Regression Coefficient

\( \epsilon \) = Residual
\( B_0 \) was verified as being 0.00. \( \beta_1 \) was verified as being approximately 1.00. No significant residual value was found.

Although the factors affecting an individual flight segment may be unpredictable, the collective effects of airport congestion, seasonal weather, air traffic control delays, and even direct routing advantages are all incorporated into the historic data. Successfully and appropriately utilizing the historic data prior to entering it into a general, predictive model for block times is the key to higher accuracy.
CHAPTER 3: RESULTS

3.1 New Model Results

The variance of the distributions created by plotting the difference between the predicted block times and the actual block times for both Southwest Airline’s current estimation method and the presented new method were compared and show that the variances, network-wide, can be reduced and minimized with an easily implementable methodology that is customizable to other networks and aircraft fleets.

Taking the third quarter, 2010, months of July, August, and September, an average block time was calculated for each city pair in Southwest Airlines’ network, for each day of the week, for three, selected time periods. The associated nomenclature follows.

Data Sets:

\(Y\) Year, indexed by \(y \in Y\)

\(Q\) Quarter year period, indexed by \(q \in Q\)

\(D\) Day of the week, indexed by \(d \in D\)

\(T\) Time period within any day, indexed by \(t \in T\)

\(C\) Origin and Destination city pair, indexed by \(c \in C\)

\(N\) Numbered occurrence of a flight segment, indexed by \(n \in N\)
Data:

\( b_{yqdtcn} \) Actual block time of flight flown between city pair, \( c \), in time period, \( t \), on day, \( d \), during quarter, \( q \), of year, \( y \).

\( n_{yqdtcn} \) Numbered occurrence of a flight segment between city pair, \( c \), in time period, \( t \), on day, \( d \), during quarter, \( q \), of year, \( y \).

\[
\text{Average} \ b_{yqdtcn} (c) = \left( \sum_{n=1}^{N} b_{yqdtcn} \right) / \left( N_{yqdc} \right)
\]

The above equation simply calculates the average, actual block time for a flight segment between a specific city pair for the designated time period on a specific day of a yearly quarter (three month time period). For this research, the single year, 2010, was selected. The resulting average block time for each city pair in the designated time period, day, and quarter of 2010 was used as the predicted block time for each corresponding flight in 2011 for the separate months of July and August.

Airline On-Time Performance data was obtained for the third quarter months of July and August, 2011, from the BTS, RITA website, as it was for the 2010 data. This research was accomplished prior to the publication of the September 2011 data, but the new prediction model may be applied to any time period within the respective quarter. These data were sorted by airline, day of the week, departure time of day, length of flight (long-haul or short-haul), and city pair. Each day of the week was divided into three flight departure time periods to match the 2010 data:
- Scheduled Departures Prior to 1000
- Scheduled Departures After 0955 and Before 2000
- Scheduled Departures After 1955

Southwest Airlines uses a selected value from the distribution of historic, actual, block times gathered for a selected quarter over a chosen time period. This selected value is applied as the predicted value to all occurrences of a specific flight segment for the entire forecast, quarter, time period. As this is the case, the Southwest Airlines predicted average block time for a specific flight segment for any time period within a designated quarter will be constant and match the calculated value resulting from the following equation.

\[
\text{SWA Average Predicted } b_{yqc}(c) = \left( \frac{\sum_{n=1}^{N_yqct} \text{predicted } b_{yqc_n}}{N_yqct} \right)
\]

3.2 Predicted v. Actual Block Times: Summarized Data

For each, individual Southwest Airlines flight, a table containing the actual elapsed block times, the Southwest Airlines predicted block time, and the predicted block time based on this research was created. The differences between the predicted and actual block times were calculated, and statistically analyzed. The standard deviation of the distribution of the differences between the predicted block time and actual block time for each city pair flown during July and August of 2011 by Southwest Airlines follows.
Standard Deviation = \left\{ \sum (\text{Average } b(c) - b_{nctdqy})^2 \right\}^{1/2} / (n - 1)

Appendix A contains the resulting comparison charts, and these comparisons are summarized in the following tables.

### July and August, 2011

#### LONG-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>8.947</td>
<td>8.97</td>
<td>0.5784</td>
<td>8.163</td>
<td>-0.807</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>9.563</td>
<td>11.14</td>
<td>0.1925</td>
<td>10.04</td>
<td>-1.1</td>
</tr>
<tr>
<td>After 1955</td>
<td>14.85</td>
<td>10.29</td>
<td>-0.1521</td>
<td>8.143</td>
<td>-2.147</td>
</tr>
</tbody>
</table>

Table 2: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Mondays (June and July, 2011)

### July and August, 2011

#### SHORT-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>4.427</td>
<td>6.123</td>
<td>0.5497</td>
<td>5.929</td>
<td>-0.194</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>3.722</td>
<td>7.704</td>
<td>0.1629</td>
<td>7.502</td>
<td>-0.202</td>
</tr>
<tr>
<td>After 1955</td>
<td>7.498</td>
<td>8.222</td>
<td>-0.1912</td>
<td>6.299</td>
<td>-1.923</td>
</tr>
</tbody>
</table>

Table 3: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Mondays (June and July, 2011)
To obtain the summarized data in Table 2, the actual block times for long-haul flights occurring in each, partitioned time period on Mondays for July and August of 2011 were subtracted, individually, from the block times predicted by Southwest Airlines, and the resulting distributions plotted. The same, actual block times for the long-haul, Monday flights were also subtracted from the block times predicted using the new model, and the resulting distributions plotted. The same process was repeated using the short-haul flights occurring in each partitioned time period on Mondays for July and August of 2011 to obtain the summarized data in Table 3. The statistical mean and standard deviation for each distribution appears in the table. The large difference in the means between the sets of distributions can be attributed Southwest Airlines added time buffer determined via a chosen statistical value in the distribution of historic, actual block times for the purpose of minimizing late arrivals. The standard deviation differences are the focal point. All three time periods show a reduced standard deviation, with the time period after 1955 (7:55 PM) displaying the largest reduction for both the long-haul and short-haul flights. The process described above was repeated to obtain the summarized data for long-haul and short-haul flights occurring on Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday.

Tables 4 through 15 display the summarized data for each partitioned time period for long-haul and short-haul flights occurring on each day during July and August of 2011. As with the results from the Monday flights previously discussed, all standard deviations were reduced, with the time period after 1955 displaying the largest reduction.
### July and August, 2011  
**Tuesday**

#### LONG-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>8.948</td>
<td>8.728</td>
<td>1.128</td>
<td>8.165</td>
<td>-0.563</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>9.234</td>
<td>11.54</td>
<td>-0.116</td>
<td>10.77</td>
<td>-0.77</td>
</tr>
<tr>
<td>After 1955</td>
<td>14.06</td>
<td>11.53</td>
<td>-0.5356</td>
<td>9.94</td>
<td>-1.59</td>
</tr>
</tbody>
</table>

Table 4: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Tuesdays (June and July, 2011)

### July and August, 2011  
**Tuesday**

#### SHORT-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>4.206</td>
<td>5.524</td>
<td>0.8927</td>
<td>5.266</td>
<td>-0.258</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>3.555</td>
<td>8.784</td>
<td>0.2181</td>
<td>8.741</td>
<td>-0.043</td>
</tr>
<tr>
<td>After 1955</td>
<td>7.309</td>
<td>9.902</td>
<td>-0.3189</td>
<td>8.517</td>
<td>-1.385</td>
</tr>
</tbody>
</table>

Table 5: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Tuesdays (June and July, 2011)
### Long-Haul Flights

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>8.584</td>
<td>8.792</td>
<td>0.8153</td>
<td>8.226</td>
<td>-0.566</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>9.447</td>
<td>10.81</td>
<td>0.3934</td>
<td>9.949</td>
<td>-0.861</td>
</tr>
<tr>
<td>After 1955</td>
<td>14.29</td>
<td>10.71</td>
<td>-0.2609</td>
<td>9.279</td>
<td>-1.431</td>
</tr>
</tbody>
</table>

Table 6: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Wednesdays (June and July, 2011)

### Short-Haul Flights

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>4.026</td>
<td>6.047</td>
<td>0.631</td>
<td>5.787</td>
<td>-0.26</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>4.003</td>
<td>6.726</td>
<td>0.75</td>
<td>6.563</td>
<td>-0.163</td>
</tr>
<tr>
<td>After 1955</td>
<td>7.646</td>
<td>8.048</td>
<td>-0.08764</td>
<td>6.32</td>
<td>-1.728</td>
</tr>
</tbody>
</table>

Table 7: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Wednesdays (June and July, 2011)
LONG-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>8.019</td>
<td>9.374</td>
<td>0.3465</td>
<td>9.102</td>
<td>-0.272</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>8.787</td>
<td>10.95</td>
<td>0.3146</td>
<td>10.26</td>
<td>-0.69</td>
</tr>
<tr>
<td>After 1955</td>
<td>13.98</td>
<td>10.3</td>
<td>-0.7716</td>
<td>9.122</td>
<td>-1.178</td>
</tr>
</tbody>
</table>

Table 8: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Thursdays (June and July, 2011)

SHORT-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>3.375</td>
<td>7.222</td>
<td>0.09854</td>
<td>7.164</td>
<td>-0.058</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>3.07</td>
<td>8.596</td>
<td>0.4015</td>
<td>8.472</td>
<td>-0.124</td>
</tr>
<tr>
<td>After 1955</td>
<td>6.585</td>
<td>9.044</td>
<td>-0.7465</td>
<td>7.838</td>
<td>-1.206</td>
</tr>
</tbody>
</table>

Table 9: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Thursdays (June and July, 2011)
### Table 10: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Fridays (June and July, 2011)

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>7.891</td>
<td>9.635</td>
<td>-0.3561</td>
<td>9.281</td>
<td>-0.354</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>8.933</td>
<td>11.92</td>
<td>-0.3516</td>
<td>11.21</td>
<td>-0.71</td>
</tr>
<tr>
<td>After 1955</td>
<td>13.71</td>
<td>10.94</td>
<td>-0.181</td>
<td>9.175</td>
<td>-1.765</td>
</tr>
</tbody>
</table>

### Table 11: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Fridays (June and July, 2011)

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>3.832</td>
<td>5.968</td>
<td>0.3561</td>
<td>5.868</td>
<td>-0.1</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>3.487</td>
<td>7.819</td>
<td>0.3437</td>
<td>7.749</td>
<td>-0.07</td>
</tr>
<tr>
<td>After 1955</td>
<td>6.592</td>
<td>7.411</td>
<td>-0.06549</td>
<td>5.994</td>
<td>-1.417</td>
</tr>
</tbody>
</table>
### July and August, 2011 Saturday

#### LONG-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>9.026</td>
<td>8.212</td>
<td>0.3143</td>
<td>7.583</td>
<td>-0.629</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>9.956</td>
<td>10.28</td>
<td>-0.2535</td>
<td>9.354</td>
<td>-0.926</td>
</tr>
<tr>
<td>After 1955</td>
<td>13.93</td>
<td>9.172</td>
<td>1.878</td>
<td>7.044</td>
<td>-2.128</td>
</tr>
</tbody>
</table>

Table 12: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Saturdays (June and July, 2011)

#### SHORT-HAUL

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>4.704</td>
<td>5.661</td>
<td>0.01881</td>
<td>5.553</td>
<td>-0.108</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>4.703</td>
<td>6.77</td>
<td>-0.2187</td>
<td>6.323</td>
<td>-0.447</td>
</tr>
<tr>
<td>After 1955</td>
<td>5.503</td>
<td>7.133</td>
<td>-1.238</td>
<td>6.63</td>
<td>-0.503</td>
</tr>
</tbody>
</table>

Table 13: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Saturdays (June and July, 2011)
### July and August, 2011 - Sunday

#### Long-Haul Flights

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>9.638</td>
<td>9.374</td>
<td>0.2681</td>
<td>8.807</td>
<td>-0.567</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>9.343</td>
<td>11.39</td>
<td>-0.1508</td>
<td>10.22</td>
<td>-1.17</td>
</tr>
<tr>
<td>After 1955</td>
<td>15.16</td>
<td>12.85</td>
<td>-0.2011</td>
<td>11.22</td>
<td>-1.63</td>
</tr>
</tbody>
</table>

Table 14: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Long-Haul Flights Operated on Sundays (June and July, 2011)

#### Short-Haul Flights

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>SWA Mean (min)</th>
<th>SWA Std Dev (min)</th>
<th>New Mean (min)</th>
<th>New Std Dev (min)</th>
<th>Change in Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before 1000</td>
<td>4.583</td>
<td>6.14</td>
<td>0.1731</td>
<td>6.085</td>
<td>-0.055</td>
</tr>
<tr>
<td>After 0955 &amp; Before 2000</td>
<td>3.37</td>
<td>8.797</td>
<td>-0.3388</td>
<td>8.691</td>
<td>-0.106</td>
</tr>
<tr>
<td>After 1955</td>
<td>6.975</td>
<td>10.73</td>
<td>-0.861</td>
<td>9.275</td>
<td>-1.455</td>
</tr>
</tbody>
</table>

Table 15: Summarized Change in Mean and Standard Deviation of Predicted Minus Actual Block Times for Short-Haul Flights Operated on Sundays (June and July, 2011)
Table 16 summarizes Tables 2 through 15, by providing the average change in standard deviation resulting from the new model for block time prediction for both the long-haul and short-haul flights occurring in July and August of 2011. Without exception, the standard deviation was reduced for every city pair in Southwest Airlines’ network with the largest reductions occurring with the long-haul flights departing after 1955.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Long-Haul Change in Std Dev (min):</td>
<td>-1.04</td>
</tr>
<tr>
<td>Average Short-Haul Change in Std Dev (min):</td>
<td>-0.562</td>
</tr>
</tbody>
</table>

Table 16: Average Change in the Standard Deviation of Predicted Versus Actual Block Time Distributions Using the New Model

3.3 On-Time Performance and Increased, Published Block Times

The following distributions of predicted minus actual block times illustrate the importance of choosing the appropriate, historic, data segments as the foundation of block time predictions. The standard deviations of the distributions using the new, generated predictions for block times are consistently less than the distributions using the Southwest Airlines predicted block times minus the actual block times, even when the new predicted block times are padded by 5 or 10 minutes. The following distributions show that by padding the new, predicted block times by 5 minutes and 10 minutes, respectively, network-wide, only the mean is affected. The standard deviation of each distribution of the new predicted block times plus padding minus the actual block times remains unchanged. These standard deviations are consistently less than those of the
distributions using the Southwest Airlines predicted block times minus the actual block times.

Figure 5 displays the distribution of the differences between the published Southwest Airlines predicted block times minus the actual block times for the short-haul flights departing on Mondays before 1000 during the third quarter of 2011.

**Monday, Short Haul Comparisons, Departures Before 1000**

![Histogram showing distribution of differences between Southwest Airlines predicted block times and actual block times for short-haul flights departing on Mondays before 1000 during the third quarter of 2011.](image)

**Figure 5**: Southwest Airlines Predicted Block Times Minus Actual Block Times

For comparison, figure 6 displays the distribution of the differences between the predicted block times generated using the new model minus the actual block times for the short-haul flights departing on Mondays before 1000 during the third quarter of 2011. Again, the mean in figure 5 differs significantly from the mean in figure 6 because of Southwest Airlines’ current method of providing a time buffer in their predicted block
times. As previously stated, the standard deviations are the focal points, and the reduction in each standard deviation is significant.

![Histogram showing the differences between new and actual block times](image)

**Figure 6:** New, Predicted Block Times Minus Actual Block Times

In figure 7, five minutes were added to all predicted block times generated with the new model, then the actual block time was subtracted prior to plotting these differences. Although the mean reflects this 5 minute addition, the standard deviation remains the same as in figure 6. Figure 8 reiterates these results and displays the outcome when ten minutes were added to all predicted block times generated with the new model before subtracting the actual block times for the short-haul flights occurring before 1000 on Mondays during the third quarter of 2011.
This exercise was repeated for all time periods for each day of the week for both long-haul and short-haul flights. A sample group of data from one time period for each day of the week follows in figures 9 through 32 to further validate the previously described results.

**Monday, Short Haul Comparisons, Departures Before 1000, continued**

![Histogram showing the distribution of New, Predicted Block Times +5 Minutes Minus Actual Block Times for 2011 Monday SHORT Departures Before 1000.]

Figure 7: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Figure 8: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Tuesday, Long Haul Comparisons, Departures After 0955 and Before 2000

Figure 9: Southwest Airlines Predicted Block Times Minus Actual Block Times
Tuesday, Long Haul Comparisons, Departures After 0955 and Before 2000, continued

Figure 10: New, Predicted Block Times Minus Actual Block Times

Figure 11: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Tuesday, Long Haul Comparisons, Departures After 0955 and Before 2000, continued

Figure 12: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Wednesday, Long Haul Comparisons, Departures After 1955

Figure 13: Southwest Airlines Predicted Block Times Minus Actual Block Times
Wednesday, Long Haul Comparisons, Departures After 1955, continued

Figure 14: New, Predicted Block Times Minus Actual Block Times

Figure 15: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Wednesday, Long Haul Comparisons, Departures After 1955, continued

Figure 16: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Thursday, Short Haul Comparisons, Departures After 1955

Figure 17: Southwest Airlines Predicted Block Times Minus Actual Block Times
Thursday, Short Haul Comparisons, Departures After 1955, continued

Figure 18: New, Predicted Block Times Minus Actual Block Times

Figure 19: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Thursday, Short Haul Comparisons, Departures After 1955, continued

Figure 20: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Friday, Short Haul, Departures After 0955 and Before 2000

Figure 21: Southwest Airlines Predicted Block Times Minus Actual Block Times
Friday, Short Haul, Departures After 0955 and Before 2000, continued

Figure 22: New, Predicted Block Times Minus Actual Block Times

Figure 23: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Friday, Short Haul, Departures After 0955 and Before 2000, continued

Figure 24: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Saturday, Long Haul, Departures Before 1000

Figure 25: Southwest Airlines Predicted Block Times Minus Actual Block Times
Saturday, Long Haul, Departures Before 1000, continued

Figure 26: New, Predicted Block Times Minus Actual Block Times

Figure 27: New, Predicted Block Times +5 Minutes Minus Actual Block Times
Saturday, Long Haul, Departures Before 1000, continued

Figure 28: New, Predicted Block Times +10 Minutes Minus Actual Block Times

Sunday, Short Haul, Departures After 0955 and Before 2000

Figure 29: Southwest Airlines Predicted Block Times Minus Actual Block Times
Figure 30: New, Predicted Block Times Minus Actual Block Times

Sunday, Short Haul, Departures After 0955 and Before 2000, continued

Figure 31: New, Predicted Block Times +5 Minutes Minus Actual Block Times
3.4 Specific Example of Increased Block Time Prediction Accuracy

The following example using the Oakland, California to Albuquerque, New Mexico (OAKABQ) city pair reinforces the result that increased block time prediction accuracy is accomplished using the new method. The distributions of actual block time data used currently as the base of future block time predictions by Southwest Airlines often have a smaller standard deviation than the chosen sets of actual block time data used in making the new predictions. Restated, greater prediction accuracy was attained using a more selective set of data that, in many cases, has a larger standard deviation than the distributions used currently by Southwest Airlines as the foundation of their predictions.
As a reference for comparison, figure 33 is given, and contains the distribution of the actual block times occurring during the third quarter months of 2009 and 2010 for all Southwest Airlines flights between Oakland, California and Albuquerque, New Mexico.

The following figure 34 displays the distribution of actual block times for Southwest Airlines flights departing at 0615 during the third quarter of 2009 and 2010. Southwest Airlines based their block time predictions for the third quarter of 2011 for their 0550 and 0600 flight departures from Oakland to Albuquerque on the 2009 and 2010 departures that occurred at 0615, as there were no flights exactly matching the new departure times scheduled for 2011 for this city pair. The mean, actual block time for this set of data is 133.5 minutes between Oakland and Albuquerque with a standard deviation of 5.73 minutes.
Southwest Airlines used this described distribution to make the block time prediction of 140 minutes for all 0550 OAKABQ departures, and 135 minutes for all 0600 OAKABQ departures for the third quarter of 2011. These are also the Southwest Airlines-predicted block times published for all scheduled OAKABQ flights for this quarter, as shown in Figure 35.

![SWA Distribution of OAKABQ Actual Block Times, Third Quarter, 2009 and 2010, 0615 Scheduled Departure Time](image)

Figure 34: SWA Distribution of OAKABQ Actual Block Times, Third Quarter, 2009 and 2010, 0615 Scheduled Departure Time
Figure 35: SWA Distribution of OAKABQ Predicted Block Times, Third Quarter, 2011, All Scheduled Departure Times

As a reference, the following chart, figure 36, shows the distribution of the actual block times that occurred for all OAKABQ flights that occurred in July or August of 2011.
3.5 Specific Example Actual Block Time Distributions and Results

The following charts, figures 37 through 43, show the distributions of the OAKABQ actual block times for scheduled departures prior to 1000 for each, individual day of the week for July, August, and September (third quarter) of 2010. These are the actual distributions, not the predicted distributions. Many of the standard deviations of these distributions are greater than those of the distributions of block times used by Southwest Airlines as the basis of their predictions. Figure 34, previously discussed, provides the distribution of actual block times from which Southwest Airlines based their predicted block times for the third quarter of 2011 for the earliest flights for the
OAKABQ city pair. The standard deviation of the distribution shown in figure 34 is 5.70 minutes. The actual block time distributions that were used as the foundation of the new prediction model have standard deviations ranging from 4.030 minutes to 7.483 minutes, but result in a distribution of predicted block times minus actual block times having a smaller standard deviation.

![Figure 37: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010](image_url)
Figure 38: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010

Figure 39: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010
Figure 40: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010

Figure 41: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010
Figure 42: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010

Figure 43: Distribution of OAKABQ Actual Block Times, Third Quarter, 2010
By padding the new, predicted block times, network-wide, by 5 minutes and 10 minutes, respectively, only the mean is affected. The standard deviation of the distributions of the new, predicted block times plus padding minus the actual block times remains unchanged. These standard deviations are consistently less than the distributions using the Southwest Airlines predicted block times minus the actual block times. This reduction in the standard deviations was attained based on historic, actual, block time distributions that, in many cases, have greater standard deviations.

Figure 44: Distribution of OAKABQ All Southwest Airlines Flights, Actual Block Times, Third Quarter, 2009-2010
CHAPTER 4: CONCLUSION

4.1 Financial Implications

The Air Transport Association of America (ATA), recently renamed Airlines for America (A4A), reported that combined fuel and labor costs account for at least half of most airlines’ operating costs (ATA, 2012), and both are greatly affected by the ability to predict accurate block times. Other variable costs affected include aircraft maintenance and aircraft ownership or leasing costs. Table 17 provides the ATA-published, average, direct costs per minute for U.S. domestic passenger airlines for 2010.

<table>
<thead>
<tr>
<th>Calendar Year 2010</th>
<th>Direct Aircraft Operating Costs per Block Minute</th>
<th>Δ vs. 2009</th>
<th>2010 Delay Costs ($ millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel</td>
<td>$28.57</td>
<td>14.80%</td>
<td>$2,838</td>
</tr>
<tr>
<td>Crew - Pilots/Flight Attendants</td>
<td>15.04</td>
<td>3.00%</td>
<td>1,494</td>
</tr>
<tr>
<td>Maintenance</td>
<td>11.01</td>
<td>1.70%</td>
<td>1,093</td>
</tr>
<tr>
<td>Aircraft Ownership</td>
<td>8.07</td>
<td>-2.00%</td>
<td>801</td>
</tr>
<tr>
<td>Other</td>
<td>2.5</td>
<td>2.40%</td>
<td>248</td>
</tr>
<tr>
<td><strong>Total DOCs</strong></td>
<td><strong>$65.19</strong></td>
<td><strong>6.90%</strong></td>
<td><strong>$6,475</strong></td>
</tr>
</tbody>
</table>

Notes:
1. Costs based on DOT Form 41 data for U.S. scheduled passenger airlines
2. Arrival delay minutes (Arr:00) reflect operations at 77 U.S. airports as captured in the FAA ASPM database

Table 17: 2010 Airline Direct Operating Costs per Minute (ATA, 2012)
Table 18 contains a list of U.S. airline bankruptcies occurring from 2000 until the end of 2011. Survival of any scheduled air carrier operating in today’s economic climate must provide safe, reliable service while minimizing all possible costs. Business innovation can widen a profit margin, but with respect to airlines, extremely lean operations must be in place without compromising safety to create any significant profit margin at all. The block time prediction model and methodology created during this research has the potential to save each, individual airline tens of millions of dollars (U.S.) per year, every year.

<table>
<thead>
<tr>
<th>COMPANY</th>
<th>START</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMR's American Airlines</td>
<td>11/29/2011</td>
</tr>
<tr>
<td>Frontier</td>
<td>4/11/2008</td>
</tr>
<tr>
<td>Skybus</td>
<td>4/7/2008</td>
</tr>
<tr>
<td>ATA</td>
<td>4/3/2008</td>
</tr>
<tr>
<td>Aloha</td>
<td>3/20/2008</td>
</tr>
<tr>
<td>FLYi Inc’s Independence Air</td>
<td>11/7/2005</td>
</tr>
<tr>
<td>Delta Air Lines</td>
<td>9/14/2005</td>
</tr>
<tr>
<td>Northwest Airlines</td>
<td>9/14/2005</td>
</tr>
<tr>
<td>Aloha</td>
<td>1/3/2005</td>
</tr>
<tr>
<td>Aloha Airgroup, Inc.</td>
<td>12/30/2004</td>
</tr>
<tr>
<td>US Airways, Inc.</td>
<td>9/12/2004</td>
</tr>
<tr>
<td>Hawaiian Airlines</td>
<td>3/21/2003</td>
</tr>
<tr>
<td>UAL Corp.’s United Air Lines</td>
<td>12/9/2002</td>
</tr>
<tr>
<td>US Airways, Inc.</td>
<td>8/11/2002</td>
</tr>
<tr>
<td>Vanguard Airlines, Inc.</td>
<td>7/30/2002</td>
</tr>
<tr>
<td>International Total Services</td>
<td>9/13/2001</td>
</tr>
<tr>
<td>Midway Airlines Corp.</td>
<td>8/13/2001</td>
</tr>
<tr>
<td>Trans World Airlines, Inc.</td>
<td>1/10/2001</td>
</tr>
<tr>
<td>Fine Air Services Corp.</td>
<td>9/27/2000</td>
</tr>
<tr>
<td>Kitty Hawk, Inc.</td>
<td>5/1/2000</td>
</tr>
<tr>
<td>Tower Air, Inc.</td>
<td>2/29/2000</td>
</tr>
</tbody>
</table>

Table 18: U.S. Airline Bankruptcies, 2000-2011 (Fox Business, 2011)
Southwest Airlines’ level of potential savings per year by implementing the new prediction model is well over $50 million (U.S.), and, as they use a single aircraft type for their operations, is easily reckoned. An average Boeing 737NG (737-700/800) burns approximately 6,000 pounds of jet fuel per hour in cruise flight (3,000 pounds per hour per engine). This equates to approximately 15 gallons of fuel per minute. Older models of the Boeing 737 aircraft have an hourly fuel consumption rate closer to 7,000 pounds per hour during cruise flight (approximately 17 gallons per minute). As of September 30th, 2011, Southwest Airlines was operating a fleet of 559 aircraft, comprised of the Boeing 737-300, 737-500, 737-700, and 737-800 models, to fly more than 3,300 flight segments per day (Southwest Airlines, 2012). With respect to fuel costs alone, a one minute reduction in the standard deviation of the predicted minus actual block times distribution for each city pair, network-wide, corresponds to a conservative estimate of an increase in accuracy of 3,300 minutes per day, representing at least 49,500 gallons of fuel daily. At minimum, this corresponds to approximately $170,000 per day (assuming a cost of only $3.50 per gallon of Jet A fuel), and over $60,000,000 per year in estimated fuel variable costs.

Reduced standard deviations in the predicted minus actual block time distributions either saves direct costs or, in the case of a flight with a greater than predicted block time, turn-around time, which, as mentioned previously, is the time at the gate between successive flights. The greater the difference between the predicted and actual block time, the greater the likelihood of aircraft having to wait for an open gate. If any flight has to wait for a gate to open, this translates directly to fuel. If a gate is available, an early arrival will decrease the actual fuel used compared to planned, but
there is also the unnecessary cost of transporting too much fuel from point A to point B due to anticipating the longer block time. The most expensive fuel onboard an aircraft is the amount used last or not at all, because fuel consumption to transport a heavier load of fuel is greater. Conversely, if a flight has a greater than predicted block time, more fuel than planned was likely required and turn-around time is at stake to avoid a subsequent, late departure. This latter scenario is not directly fuel related, but does substantially impact operations. “Studies show that adding 10 minutes to each, current Southwest Airlines turn-around time would erase 1/3 of its profits,” (Phillips, 1997).

With respect to combined, variable, operating costs, if the total, average, direct operating cost per minute provided by ATA, and shown in table 17, is applied to Southwest Airlines’ operations, then a one minute reduction in the standard deviation of the predicted minus actual block times distribution represents over $200,000 per day and over $78,000,000 per year.

4.2 Summary

A new model has been created and shown to more accurately predict airline block times between individual city pairs. These results have also been directly correlated to substantial financial savings. Airline business models, and their resulting networks of operations, are extremely complex with most operational components intertwined and the product perishable. Although technology is providing greater and greater ability to simultaneously solve and optimize for the multitude of operations-related variables, and advancing to be able to do so in real time, it is necessary to decipher what components
should be solved simultaneously. Increasing the complexity and capability of academic models will not provide reasonable or usable results without a complete and intimate understanding of the variables and data. Attempting to create an academic model encompassing everything from crew scheduling optimization to passenger demand forecasting and total profit generation is academically impressive, but not realistic nor accurate from an actual operations viewpoint. Data mining is becoming increasingly important, and the availability and quantity of data are becoming overwhelming. The opportunity to build upon the knowledge embedded in airline operations data, then selectively apply that information within appropriate, academic models, will yield the needed, practical solutions. Intertwined components should not, necessarily, be optimized simultaneously.

As previously stated, accurate block time predictions directly affect crew scheduling, aircraft maintenance scheduling, airport gate scheduling, airport congestion, and fuel purchasing decisions and costs. This is not an all-inclusive list. Stochastic models are often used with respect to attempting to optimize components of airline operations, and most use predicted block times as input data. Block times are the core of an airline’s master schedule, and the historic data provides the probability distributions that must be generated using purely academic models for other components. Through analyzing the historic data prior to inserting these data into the new block time prediction model, the resulting probability distributions of future block times are more accurate with less variance. Using the most appropriate set of historic or predicted block times as input for other optimization models will only increase the success of those models. These
other optimization models, in turn, can now more accurately be applied to solve for huge numbers of variables, simultaneously.

Although the master schedule of flights offered by an airline is considered to be its product, the consistent, reliable, and accurate execution of the published schedule is what affects passenger demand and minimizes the need for regular schedule disruption mitigation. Passenger fare structure is, obviously, a huge factor in revenue generation, but if reliable service is not provided, the price of airfare becomes a secondary consideration. Accurate, predicted block times are the core of the master schedule from which this reliability is built.

4.3 Future Research

Airline operations are dynamic with many aspects unpredictable. Long-term planning is required, along with daily disruption mitigation and schedule recovery strategies. As technology provides the increased ability towards real-time data analysis and decision-making, optimization models will need to become dynamic and flexible to be useful. Minimizing complexity wherever possible, or justifying added complexity through substantial increased benefits, will be relevant, future challenges. Through revisiting previously developed airline optimization models that already utilize historic or predicted block times, and documenting the difference in output accuracy when more appropriate and accurate block times are used, significant, additional, financial savings could be realized. Airline schedule planning and execution needs to become more flexible, and the methods and models used must be able to be updated and modified as
quickly as the technological advances are implemented in aircraft and also applied to air traffic control and communications. Planning and predicting block times many months in advance of the actual operations can be accomplished with more accurate results using the described, newly developed model, but an additional model needs to be incorporated to monitor and update these predictions based on current events without negatively affecting the many, intertwined components connected to and determined by these predictions. With the tenuous financial situations of most airlines operating today, developing the ability to extract and apply the information embedded in the plentiful and growing supply of historic and real-time data to more accurately forecast long-term operations, as well as to dynamically adapt to current situations, is imperative.


Bureau of Transportation Statistics, “Data Review: Employment in the Airline Industry,”
_Bureau of Transportation Statistics Journal of Transportation Statistics_, Vol. 8, No. 1,
2005.


APPENDIX A: PREDICTION COMPARISON CHARTS

(Third Quarter, 2011, July, August, Monday through Sunday)
Figure A.1: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.2: New Block Time Predictions Minus Actual Block Times
Figure A.3: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.4: New Block Time Predictions Minus Actual Block Times
Figure A.5: New Block Time Predictions (with an Added 5 Minutes) Minus Actual Block Times

Figure A.6: New Block Time Predictions (with an Added 10 Minutes) Minus Actual Block Times
Figure A.7: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.8: New Block Time Predictions Minus Actual Block Times
Figure A.9: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.10: New Block Time Predictions Minus Actual Block Times
Figure A.11: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.12: New Block Time Predictions Minus Actual Block Times
Figure A.13: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.14: New Block Time Predictions Minus Actual Block Times
Figure A.15: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.16: New Block Time Predictions Minus Actual Block Times
Figure A.17: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.18: New Block Time Predictions Minus Actual Block Times
Figure A.19: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.20: New Block Time Predictions Minus Actual Block Times
Figure A.21: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.22: New Block Time Predictions Minus Actual Block Times
Figure A.23: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.24: New Block Time Predictions Minus Actual Block Times
Figure A.25: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.26: New Block Time Predictions Minus Actual Block Times
Figure A.27: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.28: New Block Time Predictions Minus Actual Block Times
Figure A.29: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.30: New Block Time Predictions Minus Actual Block Times
Figure A.31: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.32: New Block Time Predictions Minus Actual Block Times
Figure A.33: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.34: New Block Time Predictions Minus Actual Block Times
Figure A.35: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.36: New Block Time Predictions Minus Actual Block Times
Figure A.37: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.38: New Block Time Predictions Minus Actual Block Times
Figure A.39: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.40: New Block Time Predictions Minus Actual Block Times
Figure A.41: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.42: New Block Time Predictions Minus Actual Block Times
Figure A.43: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.44: New Block Time Predictions Minus Actual Block Times
Figure A.45: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.46: New Block Time Predictions Minus Actual Block Times
Figure A.47: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.48: New Block Time Predictions Minus Actual Block Times
**Figure A.49:** Southwest Airlines Block Time Predictions Minus Actual Block Times

**Figure A.50:** New Block Time Predictions Minus Actual Block Times
Figure A.51: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.52: New Block Time Predictions Minus Actual Block Times
Figure A.53: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.54: New Block Time Predictions Minus Actual Block Times
Figure A.55: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.56: New Block Time Predictions Minus Actual Block Times
Figure A.57: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.58: New Block Time Predictions Minus Actual Block Times
Figure A.59: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.60: New Block Time Predictions Minus Actual Block Times
Figure A.61: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.62: New Block Time Predictions Minus Actual Block Times
Figure A.63: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.64: New Block Time Predictions Minus Actual Block Times
**Figure A.65**: Southwest Airlines Block Time Predictions Minus Actual Block Times

**Figure A.66**: New Block Time Predictions Minus Actual Block Times
Figure A.67: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.68: New Block Time Predictions Minus Actual Block Times
Figure A.69: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.70: New Block Time Predictions Minus Actual Block Times
Figure A.71: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.72: New Block Time Predictions Minus Actual Block Times
Figure A.73: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.74: New Block Time Predictions Minus Actual Block Times
Figure A.75: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.76: New Block Time Predictions Minus Actual Block Times
Figure A.77: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.78: New Block Time Predictions Minus Actual Block Times
Figure A.79: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.80: New Block Time Predictions Minus Actual Block Times
Figure A.81: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.82: New Block Time Predictions Minus Actual Block Times
Figure A.83: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.84: New Block Time Predictions Minus Actual Block Times
Figure A.85: Southwest Airlines Block Time Predictions Minus Actual Block Times

Figure A.86: New Block Time Predictions Minus Actual Block Times