# A METHODOLOGY FOR EVALUATING ECONOMIC AND POLICY IMPACTS ON AIRLINE AND PASSENGER BEHAVIOR

by

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A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Systems Engineering and Operations Research

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Spring Semester 2012
George Mason University
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# A Methodology for Evaluating Economic and Policy Impacts on Airline and Passenger Behavior

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

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# DEDICATION

I dedicate this dissertation to my wife Wilda and daughters, Julia and Devin.

## ACKNOWLEDGEMENTS

I am grateful to my advisor, Prof. Karla Hoffman, for her guidance without which I would never have made it to the end of my PhD studies. Her expertise in operations research and insight into airline scheduling molded this dissertation in unexpected ways.

Prof. Lance Sherry provided helpful insights for this research. His expert domain knowledge in air transportation helped me shape the results of my research. His availability and receptiveness to discussions at any time removed many hurdles in achieving my goal.

Prof. George Donohue contributed through his experience as a policy maker at the Federal Aviation Authority (FAA) and identified multiple beneficiaries of this research. His comments helped me identify and capture the broader implications of my work.

Prof. Mark Houck gave an outsider's viewpoint on this research. His knowledge of regression analysis assisted in clarifying the overall methodology of this research. Discussion with him helped me look at the problem from a civil engineer's perspective.

Prof. Andrew Loerch gave an outsider's viewpoint on this research. His knowledge of regression analysis assisted in clarifying the overall methodology of this research. His concerns assisted in writing a better description of the problem.

Several others have contributed to this research, Vivek Kumar, Jianfeng Wang, Guillermo Calderon; foremost among them is Abdul Qadar Kara.  Starting our research journey together at the Center for Air Transportation Systems Research (CATSR) lab, he has been a true friend to me, giving me a helping hand whenever required. I have learned most of my CPLEX and Java tricks from him and I thank him for that.

I would like to thank my family Wilda, Julia and Devin Ferguson who supported me at every stage of my pursuit of this degree and sacrificed their time with me so I could finish my research.

I would like to thank my parents Raymond and Johnnie Ferguson who supported me at every stage of my life and encouraged me to go further and reach higher goals in life.

My gratitude goes out to my mentors Dr. B N Narahari Achar, Dr. D Wayne Jones, Dr. Michael Guthrie, Col (Ret.) Brion Chabot, LTC (Ret.) Van Cunningham, Col (Ret.) Peter Nelson and LTC (Ret.) Mark Brantley who encouraged me to pursue a Ph.D.

This research was funded by The National Aeronautics and Space Administration (NASA).

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| **AIP** | Airport Improvement Program |
| **ASM** | Available Seat Miles |
| **ASOM** | Airport Schedule Optimization Model |
| **ASPM** | Aviation System Performance Metrics |
| **ATA** | Air Transport Association |
| **ATC** | Air Traffic Control |
| **ATL** | Hartsfield–Jackson Atlanta International Airport |
| **ATM** | Air Traffic Management |
| **AUS** | Austin-Bergstrom International Airport |
| **AVP** | Wilkes-Barre/Scranton International Airport |
| **BADA** | Base of Aircraft Data |
| **BDL** | Bradley International Airport |

| | |
|---|---|
| **BGM** | Greater Binghamton Airport |
| **BGR** | Bangor International Airport |
| **BIC** | Best in Class |
| **BNA** | Nashville International Airport |
| **BOS** | General Edward Lawrence Logan International Airport |
| **BTS** | Bureau of Transportation Statistics |
| **BTV** | Burlington International Airport |
| **BUF** | Buffalo Niagara International Airport |
| **BWI** | Baltimore Washington International Airport |
| **CAE** | Columbia Metropolitan Airport |
| **CASM** | Cost Per Available Seat Mile |
| **CHO** | Charlottesville-Albemarle Airport |
| **CHS** | Charleston International Airport |
| **CLL** | Easterwood Airport (College Station, TX) |
| **CVG** | Cincinnati/Northern Kentucky International Airport |
| **DAY** | James M. Cox Dayton International Airport |

| | |
|---|---|
| **DB1B** | Airline Origin and Destination Survey |
| **DCA** | Ronald Reagan Washington National Airport |
| **DEN** | Denver International Airport |
| **DFW** | Dallas/Fort Worth International Airport |
| **DOT** | Department of Transportation |
| **DSM** | Des Moines International Airport |
| **DTW** | Detroit Metropolitan Wayne County Airport |
| **EAS** | Essential Air Service |
| **ERI** | Erie International Airport |
| **EWR** | Newark Liberty International Airport |
| **FAA** | Federal Aviation Administration |
| **FAM** | Fleet Assignment Model |
| **FOC** | Flight Operating Cost |
| **GDP** | Gross Domestic Product |
| **GDS** | Global Distribution System |
| **GSP** | Greenville-Spartanburg International Airport |

**HNL** Honolulu International Airport

**HVN** Tweed New Haven Regional Airport

**IAD** Washington Dulles International Airport

**IFAM** Itinerary-Based Fleet Assignment Model

**IFR** Instrument flight rules

**IGSM** Integrated Global System Modeling

**IMC** Instrument meteorological conditions

**IND** Indianapolis International Airport

**ISD-FAM** Integrated Schedule Design and Fleet Assignment Model

**JAX** Jacksonville International Airport

**JFK** John F. Kennedy International Airport

**LCC** Low-Cost Carrier

**LGA** La Guardia Airport

**LP** Linear Programming

**MCO** Orlando International Airport

**MDT** Harrisburg International Airport

| | |
|---|---|
| **MDW** | Chicago Midway International Airport |
| **MEM** | Memphis International Airport |
| **MHT** | Manchester-Boston Regional Airport |
| **MIP** | Mixed Integer Programming |
| **MKE** | General Mitchell International Airport |
| **MLU** | Monroe Regional Airport |
| **MVFR** | Marginal Visual Flight Rules |
| **NAS** | National Airspace System |
| **NASA** | National Aeronautics and Space Administration |
| **NEXTGEN** | Next Generation Air Transportation System |
| **NEXTOR** | National Center of Excellence for Aviation Operations Research |
| **O&D** | Origin and Destination |
| **OAK** | Oakland International Airport |
| **OMA** | Omaha Epply Airport |
| **ORD** | Chicago O'Hare International Airport |
| **ORF** | Norfolk International Airport |

| | |
|---|---|
| **PFC** | Passenger Facility Charge |
| **PHL** | Philadelphia International Airport |
| **PQI** | Northern Maine Regional Airport at Presque Isle |
| **PVD** | Theodore Francis Green State Airport |
| **RASM** | Revenue per Available Seat Mile |
| **ROC** | Greater Rochester International Airport |
| **RPM** | Revenue Passenger Miles |
| **SAV** | Savannah/Hilton Head International Airport |
| **SBY** | Salisbury-Ocean City Wicomico Regional Airport |
| **SDF** | Louisville International Airport |
| **SESAR** | Single European Sky ATM Research |
| **SFO** | San Francisco International Airport |
| **SJU** | Luis Muñoz Marín International Airport |
| **SRQ** | Sarasota-Bradenton International Airport |
| **VFR** | Visual flight rules |

# ABSTRACT

A METHODOLOGY FOR EVALUATING ECONOMIC AND POLICY IMPACTS ON AIRLINE AND PASSENGER BEHAVIOR

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This dissertation describes an equilibrium model to examine domestic airline scheduling and pricing behavior in response to changes in fuel prices and runway capacity limits. A major re-design of an equilibrium model developed by Le (2006) was performed that allows one to look at the responses of the airline industry as costs change and/or as capacity limits are altered. Part of this re-design required an analysis of the sensitivity of airfares to supply changes and the development of general elasticity models for each of the major markets served by the airports in this study.

The US Government expects to spend $37 billion in order to increase airspace capacity in the US (e.g. SESAR/NextGen) while economists argue that there are market-based mechanisms that can better manage congestion at airports where expansion is

impossible and during the interim before the technologies are fully functional. Those that argue against market-based approaches worry that passengers in smaller markets will lose air-transportation access, airlines are too fragile to incur any new taxes, airfares will increase and it will not force the up-gauging that will improve throughput with current technologies. By evaluating how cost changes and/or capacity changes impact airline behavior, one can evaluate if these arguments are justified.

Airline domestic scheduling and pricing behavior is examined at eight congested airports (BOS, DFW, EWR, JFK, LGA, ORD, PHL, and SFO) because they generated 47.5% of the flight delays in 2007 and 42.6% of the flight delays in 2010. We record changes in the markets served by each of these airports, the frequency of service to these markets, changes in the aircraft size, the number of passengers served and the average airfares when fuel price are increased and when runway capacity limits are imposed. We also examine the effect of these changes on the profitability of the airline industry and the amount of fuel used.

The results of this analysis show that:

- The system is very sensitive to fuel price changes and less sensitive to capacity changes, especially between Visual Flight Rules (VFR) and Marginal Visual Flight Rules (MVFR).

- The Airport Schedule Optimization Model (ASOM) developed in this dissertation indicates that the airline industry is robust but will alter their schedules and service to maintain profitability.

- As fuel prices increase, airlines are likely to show greater changes in their schedules and the model reflects an increase in airfares, a decrease in passengers served and a decrease in aircraft gauge.

- As fuel prices start to increase operational costs are dominated by fuel costs. When this occurs, airlines no longer see the economies of scale related to aircraft size that are exhibited at lower fuel costs.

Keywords: Economic analysis, performance metrics, longitudinal analysis, airport delays, market analysis, metroplex.

# CHAPTER 1 – INTRODUCTION

## 1.1. BACKGROUND OF CONGESTION PROBLEM

The air transportation system is a significant driver of the U.S. economy, providing safe, affordable, and rapid transportation. At most airports, air transportation flight demand is below maximum available flight throughput capacity allowing any airline access to runways and enabling better on time operations unless weather or operational conditions reduce capacity substantially. However, the flight demand (and scheduled operations) at the busiest airports in the US often approaches and exceeds the flight capacity of those airports (NEXTOR et al. 2010). When schedules are not reduced to at or below the airport's maximum throughput capacity, demand outstrips supply and delays result. Equally important, delays at these busy airports propagate to other airports creating system-wide delays when crews and aircraft do not arrive at their next destination in time to allow the subsequent departure to meet its scheduled departure time (Welman et al. 2010) .

This situation is confounded by the fact that for the past three decades airport flight capacity has not grown in step with demand for air transportation (+2.0% annual growth for the past 20 years, Table 1), resulting in unreliable service and systemic delays.

Estimates of the impact of delays and unreliable air transportation service on the economy range from $32.3 B/year (NEXTOR et al. 2010) to $41B/year (C. E. Schumer and C. B. Maloney 2008).

The FAA and the airport authorities would prefer to see the airlines maximize the use of airport flight and seat throughput capacity at these high-demand airports; however the airlines have chosen in the past two decades to decrease the number of passengers per flight as shown in Table 1. Even though 39.8% more flights were flown in 2010 versus 1990 only 2.7% more seats were flown on aircraft 39.9% smaller. Given this trend, even if one were to increase the number of operations for an airport, the overall throughput might still not be equivalent to the throughput of 20 years ago. And, building new runways at our busiest airports (New York's LaGuardia, John F. Kennedy, and Newark; Chicago's O'Hare, Los Angeles's International, San Francisco's International, Boston's Logan, Atlanta's Hartsfield Airport, etc) is expensive, may not be feasible, and would, if feasible, take decades to accomplish.

**Table 1  BTS T100 Annual Domestic Flight Statistics (U.S. DOT/BTS 2010)**

| Domestic Passenger Flight Statistics | 1990 | 2010 | % change from 1990 to 2010 | Average Annual % change |
|---|---|---|---|---|
| Flights Scheduled (million) | 6.35 | 8.55 | 34.6% | 1.7% |
| Flights Flown (million) | 6.22 | 8.70 | 39.8% | 2.0% |
| Seats Flown (million) | 803.51 | 824.97 | 2.7% | 0.1% |
| Passengers Flown (million) | 448.31 | 643.80 | 43.6% | 2.2% |
| average aircraft size (seats/flight) | 126.50 | 96.49 | -23.7% | -1.2% |
| average load factor (passengers/seats) | 56% | 78% | 39.9% | 2.0% |

There are three primary approaches to increasing flight capacity in the US air transportation system.  The first is by increasing flight capacity at currently congested airports.  The Airport Improvement Program (AIP) (Kirk 2009) currently spends up to $15 billion per year on technological improvements to the air traffic control system; on research on issues related to aviation safety, mobility, and on airport facilities and runway improvements.  However, the most congested airports often lack the real estate to enable any significant runway capacity growth.

A second approach to increasing effective flight capacity of the US air transportation system is to improve the productive utilization of current capacity.  The FAA is currently modernizing the U.S. Air Traffic Control (ATC) system through a $37B program known as NextGen.(FAA 2011b)  NextGen will improve productivity and the utilization of existing airspace yielding increases in the effective-capacity of the airspace and airports.

NextGen initiatives are focused on improvements in flow management, airborne re-routing, 4-D coordination of flights, and super-dense operations that will increase the number of flights that can be handled safely within the aerospace during peak-periods.

However, this increase in capacity from NextGen is primarily accomplished during the airborne phase of flight and not by substantially improving runway capacity, since the greatest restriction of runway capacity is the spacing of aircraft during takeoff and landing and that is determined by the need to separate aircraft to prevent any ill-effects of wake-vortices.(Schroeder 2011)

**Table 2 OEP Airport changes in gauge, flights, and seats from 2005 to 2010 (U.S. DOT/BTS 2010)**

| | | | Change from 2005 to 2010 | | |
|---|---|---|---|---|---|
| Airports | 2005 avg size | 2010 avg size | Gauge | flights | seats |
| ATL | 120 | 112 | -8 | -2% | -9% |
| BOS | 97 | 103 | 6 | -9% | -4% |
| BWI | 124 | 123 | -1 | -3% | -4% |
| CLE | 70 | 69 | -1 | -24% | -25% |
| CLT | 93 | 97 | 4 | 6% | 10% |
| CVG | 72 | 69 | -3 | -68% | -69% |
| DCA | 97 | 95 | -2 | -3% | -5% |
| DEN | 102 | 105 | 3 | 14% | 17% |
| DFW | 109 | 111 | 1 | -8% | -7% |
| DTW | 95 | 89 | -7 | -11% | -17% |
| EWR | 101 | 101 | 0 | -12% | -12% |
| FLL | 132 | 142 | 9 | -18% | -13% |
| HNL | 141 | 134 | -7 | -15% | -19% |
| IAD | 74 | 90 | 16 | -40% | -27% |
| IAH | 92 | 92 | 0 | -6% | -7% |
| JFK | 133 | 119 | -13 | 14% | 3% |
| LAS | 143 | 143 | -1 | -16% | -16% |
| LAX | 119 | 126 | 7 | -9% | -4% |
| LGA | 96 | 95 | -1 | -9% | -10% |
| MCO | 133 | 143 | 11 | -13% | -6% |
| MDW | 135 | 130 | -5 | -8% | -12% |
| MEM | 76 | 69 | -7 | -9% | -17% |
| MIA | 134 | 138 | 3 | 0% | 3% |
| MSP | 102 | 101 | -2 | -18% | -19% |
| ORD | 99 | 92 | -8 | -9% | -16% |
| PDX | 100 | 102 | 2 | -9% | -7% |
| PHL | 98 | 93 | -5 | -11% | -16% |
| PHX | 124 | 129 | 5 | -18% | -14% |
| PIT | 74 | 93 | 18 | -50% | -38% |
| SAN | 121 | 131 | 10 | -12% | -5% |
| SEA | 120 | 129 | 9 | -6% | 1% |
| SFO | 123 | 123 | 0 | 17% | 17% |
| SLC | 88 | 93 | 5 | -20% | -16% |
| STL | 81 | 100 | 19 | -36% | -21% |
| TPA | 119 | 133 | 15 | -26% | -17% |
| Grand Total | 105 | 108 | 2 | -12% | -10% |

The third approach to increasing effective capacity of the US air transportation system is to improve the efficient use of current flight capacity by flying larger aircraft in each runway slot. This approach is dependent on understanding what motivates an airline to increase average aircraft sizes for operations or seats per operation, so that passenger demand can be handled with fewer flights. Table 2 shows that between 2005 and 2010, sixteen of the 35 busiest airports in the United States realized a reduction in seat capacity because of a reduced average number of seats on each aircraft for operations at the airports. Collectively these 35 airports realized a 10% decrease in seat capacity as a result of the airline scheduling and aircraft selection process. The greatest reduction in seat capacity was seen at New York's JFK airport where the average number of seats on each aircraft for operations was reduced 10%, from 133 seats per operation to 119 seats per operation. On the other hand, the Pittsburgh International Airport's average number of seats on each aircraft for operations was increased 25%, from 74 seats per operation to 93 seats per operation, during this time period. Therefore understanding the motivations behind airline fleet choices will be critical for policy makers to determine which policies or programs might incentivize airlines to up-gauge and better utilize current existing flight capacity. This understanding is critical to accurately forecast any benefits that may be realized from flight capacity or productivity improvements to the US air transportation system.

When considering the behavior of airlines, one must examine how both national economic conditions and specific operational and capital costs have impacted this industry. In the past few years, the United States has experienced several fluctuations in economic conditions which impact the air transportation system and effected airline behavior. (Ferguson et al. 2009a) One significant factor in the airlines cost structure is the significant increase in fuel costs. Airlines have attempted to pass this increase in their operational costs on to the air traveler through increased air fares and new fees such as baggage fees, food charges and other add-on fees. However, since the airline customer is highly sensitive to price, such increases in airfares and the tightening of budgets during recessionary times, has resulted in the demand for air travel decreasing. In addition, due to new communication technologies, passengers are more capable of price shopping and pushing average prices down. The airlines have responded to these economic conditions by decreasing their gauge on many flights as well as making significant changes to their schedules. Therefore an analysis of airline motivations behind fleet choices will need to include the impact of increased fuel prices.

## 1.2. Problem Statement

The United States air transportation system has experienced phenomenal growth over the past few decades as shown in Table 1. The FAA and DOT have projected continued growth for this sector of the economy, 3.7% per year for the next five years and 2.5% for the following 15 years (U.S. DOT/ FAA 2011). Given this forecast and the airline scheduling behavior over the past 20 years the following questions need to be examined:

- Can the United States air transportation system seat throughput capacity grow, in the most populated areas? This question is especially important since air transportation helps regional economic growth. Current United Stated national airspace (NAS) models are trying to predict the impact of continued domestic passenger demand growth, since FAA forecasts (FAA 2011a) project passenger demand will increase 165% and aircraft operations are projected to increase to 150% within the next 20 years.

- Are there mechanisms that will encourage airlines to up-gauge the size of aircraft at congested airports? Historical analysis (Ferguson, et al. 2010) indicates that the airline industry has been purchasing regional jets whose capacity ranges between 50 and 80 passengers and using these aircraft at capacitated airports such as LGA, DCA, BOS, ORD, ATL and PHI. Without up-gauging aircraft the airlines might not be able to service this increased passenger demand over the next 20 years.

These larger questions in the United States air transportation industry have motivated this research. This dissertation helps to inform these larger questions by answering some key questions about passenger and airline behavior in response to economic fluctuations and changes in aircraft cost and fuel efficiency.

Regulators need to understand how airlines will respond to specific changes that impact the airline industry (e.g. controlling access to runways via slot allotments, changes in landing fees, increases in fuel costs or taxes on fuel, up-gauging requirements). This research is directed to obtaining a better understanding of airline economics, and providing methodologies that predict systematic changes when policies are imposed that impacts the airline's profitability.

This research uses equilibrium modeling that includes airline cost and revenue models as well as air passenger price-response models to better understand the scheduling and aircraft selection decisions that are likely to be made when (a) airline costs increase, (b) economic conditions change and (c) when runway capacities are either increased or decreased. We will also look at the impact of what happens when these conditions occur simultaneously. Thus, we will consider a factorial design that considers the interactions among these factors.

## 1.3. Objective of this Research

The objective of this research is to inform decision-makers on how changes in airport capacity, increased airline operational costs (such as fuel prices), and aircraft performance (fuel burn rates) impact geographic access to air transportation service. By examining how airlines add or drop markets and change frequency of daily flights this research will be able to answer the following questions: (1) What happens to geographic access to air transportation services by congestion management schemes such as “caps” at certain highly-congested airports? Would such regulations result in an elimination of service at smaller markets, impact the number of passengers served, the average airfare charged for service to daily markets, and/ or the profitability of airlines? (2) Would increased operational costs from fuel prices reduce or eliminate service to smaller markets. How would changes in airline scheduling impact the number of passengers served, the average airfare charged, and the profitability of airlines?

This dissertation examines how reductions in capacity may impact a variety of metrics that measure the health of this form of transportation. Currently there are capacity restrictions on only four airports in the U.S. However, as demand increases, capacity restrictions may need to be imposed on many of the other high-demand airports such as Philadelphia (PHL), Chicago O'Hare (ORD), Washington Dulles (IAD), and San Francisco International Airport (SFO) in order to limit delays at these airports. We measure how these restrictions may impact:

- Access to these airport from smaller or economically depressed communities; we refer to this type of access as *economic access.*
- Pricing policies and schedules of the airlines; we refer to changes in airfares as *economic access* since changes in airfares impact passengers' economic ability to have access to the air transportation system.
- The profitability of the airlines that service that airport;
    - The throughput of passengers through that airport;

Similarly, we examine how increases in aviation fuel price impact the industry using the same metrics. We examine fuel prices for two reasons: (1) Increases in fuel prices can be considered as a surrogate to increases in any component of the operating costs of the airline industry, and (2) Fuel prices have increased significantly in the last few years and now dominate the total operating cost of an airline. When fuel prices increased to $3.00 per gallon, this cost made up 68% of the total operating cost. (U.S. DOT/BTS 2010) Thus, fuel prices are a significant driver in deciding the size of aircraft to use in each market served as well as the types of aircraft to purchase.

## 1.4. Research Approach

The past several years have provided an excellent opportunity to collect historic data on how airlines and passengers respond to significant changes in economic conditions, in particular fuel prices and national unemployment rates. Aviation fuel prices have ranged from $1.24 per gallon to $3.53 per gallon from 2005 to 2010. US unemployment rates have ranged from 4.4 percent to 10.0 percent from 2005 to 2010. Based on this historical data, supply and demand curves are developed with shapes that reflect such changes. These curves are then used in a macroeconomic equilibrium model to determine the likely schedules and prices airlines will choose in order to maximize profit given specific capacity limits and operational costs. The model also outputs the demand that results from such changes in airline announced schedules.

An economic equilibrium model of airline domestic scheduling and aircraft selection behavior was developed to answer questions about how changes in airport operational costs and varying capacity limits impact the air transportation. To examine these changes, the total markets served, the frequency of that service, the change in airfares, the average aircraft size, as well as the airline profitability is examined. The Airline Scheduling Optimization Model (ASOM) aggregates individual airline responses into a single airline with "benevolent" behavior. The ASOM ensures the "benevolent" airline posts prices that are consistent with current competitive prices (i.e. it does not seek monopolistic rents) and attempts to serve as many markets as it can, while remaining profitable.  Thus the model attempts to describe the airline industry as a whole, rather than the responses of individual airlines.

This ASOM is an equilibrium model maximizing profit for the aggregate "benevolent" airline by selecting the most profitable schedules for current markets served by the airline based on individual market revenues.  It looks at both supply and demand curves and considers how both schedules and aircraft sizes might change to accommodate changes in the underlying economic conditions or capacity restrictions.  The analysis is based on quarterly data and therefore describes aggregate quarterly behavior, rather than day-to-day operation cost fluctuations.

A historic analysis (2005-2009) (Ferguson et al. 2009b) (Ferguson et al. 2010) of the air transportation service was conducted to see how economic conditions (operational costs) and operational (capacity) limit changes at the New York airports impacted geographic access, economic access, airline profitability, and efficient use of the capacitated airspace  and emissions.   This analysis is used to both provide input data to the ASOM model as well as validate some of its outputs.  That is, we use historic pricing curves and demand functions and then evaluate, for that historical period, if the resulting schedules and fleet configuration are consistent with what was historically flown that period. We also use this historical analysis of passenger demand relative to airfare curves to better understand how such curves change with fluctuations in fuel price, national unemployment rates, operational limits at New York airports and seasonality on the individual market demand versus airfare curves.

The ASOM model allows for adjustments in airport operational capacity limits and in available aircraft for serving the airport's markets. The model determines the optimal daily schedule for an airport by solving a master problem which maximizes total profit at a given airport. Sub problems determine the most profitable schedules (i.e. flight times, and fleet size) for each market based on the dual prices supplied by the master problem that reflect the cost of adding/deleting flights from the schedule at a given time period. Thus, the sub problems provide feasible schedules for each market along with their resulting estimated profitability. The master problem chooses among these schedules limiting the number of flights in each time period to the capacity of the runways.

As airport operational capacity is reduced, markets will compete for capacity during the congested periods. This competition is modeled through a process called "column-generation", where individual market schedules are determined based upon determining the most profitable schedule for each market given the cost of adding/deleting flights during that time period. Whenever the master problem chooses an alternative collection of schedules, its dual prices change and these new dual prices are fed to the sub problems that again generate new schedules for each market. This process continues until there is no improvement in the objective function or there are no new schedules generated. If the final solution of the master problem is not integer, then the process continues in a branch-and-price phase whereby variables are forced to be integer at each node of the branch-and-bound tree.

Each run of this equilibrium model provides a complete description of the markets served from a given airport including the departure and arrival time of each flight, their associated revenue and costs. As runway capacity or operational costs are changed the ASOM reflects the airline responses in the schedules and airfares.

In order to the answer the questions of this study an experiment was conducted where 96 possible treatments (Eight congested airports, four fuel prices, and three airport operational rates) are considered. This experiment was conducted with baseline data for airline and passenger behavior from third quarter 2007, the most congested period in recent U.S. air transportation history. The eight airports studied in this experiment included Boston Logan International (BOS), Dallas/Fort Worth International (DFW), Newark Liberty International (EWR), New York John F. Kennedy International (JFK), New York LaGuardia (LGA), Chicago O'Hare International Airport (ORD), Philadelphia International Airport (PHL), and San Francisco International Airport (SFO). Three airport runway operational levels were considered: Visual flight rules (VFR), Marginal flight rules (MVFR), and Instrument Flight Rules (IFR). Five alternative fuel prices were used: $2, $3, $4, and $5.

## 1.5. Research Contributions

Multiple stakeholders for the US air transportation system can benefit from an understanding of airline and passenger behavior in the presence of economic and regulatory changes. This research provides a methodology and model (the ASOM) to examine these airline and passenger behaviors.

Government policy-makers will be provided a quantitative analysis of impact of changes to airline scheduling and pricing behavior that are likely to result from changes in airport capacity limits or with changes in fees. This research provides a better understanding of aircraft economies of scale and how they change due to increased fuel prices

Airline economists are provided a methodology to examine passenger demand versus airfare curves as a function of seasonality, competition, frequency of service and economic factors. These coefficients of change provide a good metric to compare an airport's sensitivity to economic changes

Airspace Researchers (e.g. NASA, Metron Aviation, Sensis, FAA) will be able to use this tool to see if new technologies (e.g. better separation rates, aircraft with better fuel or emissions efficiency) will significantly impact the number and type of passengers using the airspace as well as the predicted delays that such schedules might create.

## 1.6. Dissertation Outline

Chapter 2 of this dissertation provides a literature review of recent macroeconomic models used to examine the US air transportations system, techniques for analyzing air transportation demand versus airfare, modeling techniques for airline scheduling, and airline economics. Chapter 3 provides a detailed description of the passenger demand versus airfare curves and an approach to examining how these curves respond to economic changes. Chapter 4 provides a detailed description of the ASOM model and the analytical approach of examining airline behavior in response to operational cost and runway capacity changes. Chapter 5 describes an experiment of congested airports to determine airline scheduling and pricing behavior in response to changes in operational costs and runway capacities. Chapter 6 provides some conclusions and an insight from the experiment described in Chapter 5 and provides some opportunities for further research in this field of study.

# CHAPTER 2 – LITERATURE REVIEW

This chapter presents a review of literature on airline economics, airline fleet planning, passenger demand versus airfare models, airline fleet assignment and scheduling models, and airline macroeconomic models. This chapter provides a necessary primer on airline economic terms, concepts, and models, so that the reader can better understand the contributions presented in this dissertation.

## 2.1. The Economics that motivate airlines

The principle driver of air travel is economic growth. (Belobaba et al. 2009) The recent high water mark in the United States air transportation occurred in 2007, when US airlines emplaned 769 million passengers and commercial aviation revenues were over $170 billion or approximately 8% of the US gross domestic product.

Increased competition between Low Cost Carriers (LCCs) and Legacy carriers along with the quintupling of aviation fuel prices have incentivized the airlines to make significant cost and productivity improvements.(Belobaba et al. 2009) Airlines have increased load factors and have implemented practices consistent with the LCC business model to reduce costs. These concerted efforts by both Legacy and LCC airlines were not sufficient to offset the increased fuel prices.

Competitive pressure from LCCs, the loss of consumer confidence in the air transportation system's reliability and operating performance, and the transparency of pricing facilitated by the Internet and online travel distribution channels have all contributed to a precipitous decline in average fares and have had a significant impact on airline revenues.

### 2.1.1. Airline Revenue and Costs

The following metrics are the key building blocks for the basic airline profit equation, which is revenue minus cost. (Belobaba et al. 2009)

**Airline Operating profit = Revenue – Cost = (RPM × Yield) – (ASM × Unit cost)**

**Equation 1 Airline operating profit**

Revenue passenger miles (*RPM*) is a measure which accounts for the number of passengers who were serviced with flights to their intended destination along with the number of miles or kilometers they were transported. This is equivalent to a volume of service metric. The system is credited with one *RPM* for every mile a paying passenger is transported. When all revenue generated from the air transportation service is divided by *RPMs*, this produces a metric called *Yield*. Yield is the average fare paid by passengers, per mile flown.

In air transportation the measure of service supplied is measure as available seat miles (*ASMs*). One *ASM* is equivalent to one aircraft seat flown one mile. When all costs to supply the air transportation service are divided by *ASMs*, this produces a metric called Unit Cost. Unit cost is average operating cost per seat. This measure is also referred to as Operating Costs per ASMs (CASMs).

When more service is demanded than supplied the missed demand is called spillage. And when more service is supplied than demanded the excess service is called spoilage. The measure which tracks the percentage of spoilage an airline has is called the load factor. The average load factor for the air transportation service is calculated by dividing *RPMs* by *ASMs*.

Another measure used to determine airline profitability is called Unit Revenue, which is calculated by dividing the sum of revenue generated for the air transportation service by the *ASMs* supplied. This measure is also referred to as Revenue per *ASMs* (RASMs).

The emergence and rapid growth of “low-cost” airlines is due in large part to their ability to deliver air transportation services at substantially lower costs and at higher levels of productivity than the traditional “legacy” airlines. In response, legacy airlines have had to find ways to reduce operating costs and improve the efficiency of how they utilize both their aircraft and employees. (Belobaba et al. 2009)

Costs for air transportation service are categorized as direct or indirect, where direct costs are all those costs associated with the operation of the airplane. Flight operating costs (FOC) are measured and reported as costs per block hour of operation. And passenger service costs are measured and reported as costs per ASM.

Airline operating costs are divided into direct operating costs, ground operating costs, and system operating costs. Direct operating costs are expenses associated with operating aircraft. Direct operating costs represent the largest proportion of an airline's operating expenses and are usually allocated against the number of block hours operated by the airline's fleet. Ground operating costs are incurred at the airport stations in handling passengers, cargo and aircraft or by the airline in making reservations and ticket sales, and are directly incurred in providing transportation services to the customer. System operating costs are the indirect operating costs remaining after ground operating costs are accounted for. They are not directly associated with supplying the transportation service, but are more of a corporate overhead expense. Air transportation cost analysis for 2007 shows that flight operating costs (FOC) were 53.1%, ground operating costs were 20.5%, and system operating costs were 26.4% of total expenses for airlines. (Belobaba et al. 2009)

The LCC "Business Model" details characteristics associated with the low cost carrier's (LCC) productivity efficiencies and lower costs. Fleet commonality reduces costs of spare parts, maintenance and crew training. LCCs typically have no labor unions and lower wage rates. Single cabin service reduces complexity and costs, however this practice does not ensure reductions in revenues from airfare will not be greater than reduced costs from using a single versus a multi-cabin service. Open seating reduces costs associated with printing boarding passes and processing passengers. Elimination of food and beverages reduces unit costs. No frequent-flyer loyalty programs reduce administrator costs, but also reduce revenues. Only selling tickets from airline sources and avoiding the use of travel agencies and global distribution systems (GDS) reduces additional indirect costs from GDS fees.

## 2.2. Airline Fleet Planning

Airline strategic decisions to acquire new aircraft impact their financial position for up to 15 years due to depreciation costs. (Belobaba et al. 2009) These fleet decisions impact an airline operationally for more than 30 years, the minimum operational life of commercial aircraft.

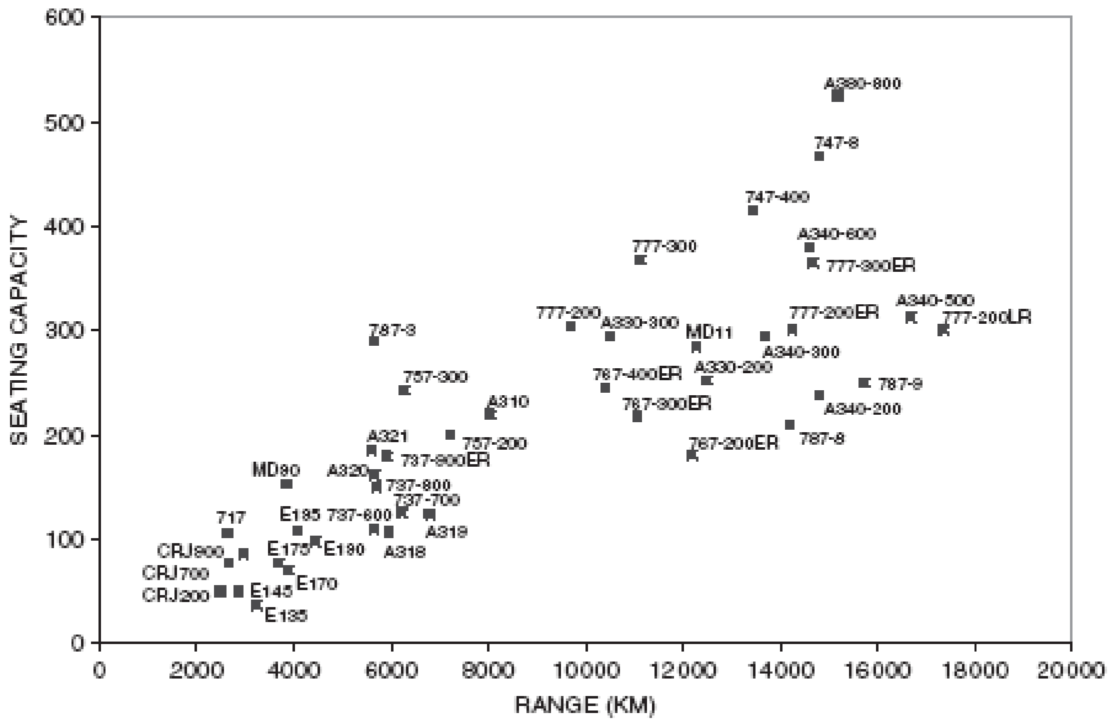



**Figure 1 Commercial Aircraft Operational Range versus Seating Capacity, figure 6.1 from (Belobaba et al. 2009)**

Commercial aircraft are commonly defined by the aircraft's range and size (seat capacity). The broad categories of "narrow body" and "wide body" aircraft, where historically "narrow body" aircraft are used for short haul markets and "wide body" aircraft are used for long haul markets. However, over the past 30 years the number of "narrow body" aircraft made available by aircraft manufacturers with greater ranges has increased substantially, as seen in Figure 1. Specifically the range capability of 100 to 150 seat aircraft has increased dramatically and now allows transcontinental routes to be flown by "narrow body" aircraft.

The current airline fleet acquisition decisions are determined first by determining individual market ASMs required, by examining future demand forecasts with targeted load factors. Next with an analysis of current fleet inventories, aircraft operational costs, expected markets yield, and assumed aircraft productivity rates, the airlines can determine aircraft acquisition requirements by aircraft size and market range. (Belobaba et al. 2009)

This dissertation's modeling approach does not consider the airlines strategic acquisition decisions or costs. The model ensures only current (within last 5 years) fleet options for markets are available for selection. This background information also helps explain some of the rationale behind airline trends on down-gauging.

## 2.3. Airport Capacity Limits

The idea of improved utilization of runway/airspace capacity through increased aircraft size gained some traction in 2007 and 2008. This resulted in new and adjusted capacity limits at the major New York and Newark airports. Specifically a Department of Transportation initiative coordinated capacity limits at the three New York airports (JFK - 81 per hour (1/18/2008), EWR - 81 per hour (5/21/2008), LGA - decreased from 75/hour + 6 unscheduled to 71/hour + 3 unscheduled (1/15/2009). The slots at each of the airports were allocated by grandfathering. (Federal Registry 2009) The concept of auctioning the slots to maximize the economic efficiency in the allocation and to ensure competitive airfares and service met strong criticism and was withdrawn.

The objections to the concept were based on concerns that the introduction of capacity limits and market-based allocation schemes would affect: (Loan Le et al. 2004)(Ball et al. 2007)

1. Geographic access to air transportation service (i.e. elimination of service at smaller markets)

2. Economic access to air transportation service (i.e. increased operational costs could lead to increased airfares, that might be too costly for certain segments of the population).

3. Airline finances in a negative manner (i.e. reduced profits due to additional costs of operation)

4. Air Transportation Efficiency as measured by the seats per runway/airspace slot (also known as aircraft size or aircraft gauge).

## 2.4. Airline Fleet Assignment and Scheduling Models

The objectives of air carriers, as commercial entities, are to optimize profit or market share. Modeling this behavior requires the understanding of airline economics and operations to create the right incentives. In scheduled passenger air transportation, airline profitability is critically influenced by the airline's ability to construct flight schedules containing flights at desirable times in profitable markets (defined by origin-destination pairs). This section describes the airline schedule development process and airline schedule optimization methods.

The terminologies for airline schedule planning are important to clarify before further discussion. (Barnhart et al. 2002) A *flight-leg* is a non-stop trip of an aircraft from an origin airport to a destination airport (one take-off and one landing). A *market* is an origin-destination airport, in which passengers wish to travel. An *itinerary* for a particular market is a sequence of flight legs, which originates at the origin airport and terminates at the destination airport. *Aircraft utilization* is the average operating hours per aircraft each day. (Belobaba et al. 2009) *Frequency share* in the airlines percentage of daily flights compared to all airlines flights for a specific market. Demand *spill* is when passenger demand is not satisfied with the supply of seats from aircraft in the flight schedule. Spill occurs when the aircraft assigned to a flight departure is too small to satisfy the potential passenger demand and therefore revenues are lost to the airline.

### 2.4.1. Airline schedule planning

In this dissertation, as the goal is to model airline scheduling practice from the perspective of an aggregated airline, the focus will be the fleet schedule development.

Airline schedule planning is a complex decision making process for the airlines which typically begins 12 months prior to the operation of the schedule and lasts up to 9 months. (Lohatepanont & Barnhart 2004) The process starts off with frequency planning where airlines determine the service requirements for all markets. Frequency planning determines how often airlines should operate flights on selected routes. (Belobaba et al. 2009) Increases in frequency for markets reduce schedule displacement or wait time between flights for travelers. These increases in frequency can also capture time sensitive business travelers. Even though fleet assignments are performed in a later step of the schedule development, it is clear that initial assumptions must be made to determine the required number of flights per market.

After frequency of service is determined the next step is to generate a timetable of flight departures. This process requires a trade-off between maximizing aircraft utilization and schedule convenience for the passengers. The timetable must include minimum turnaround times required at each airport to deplane and enplane passengers, refuel, check and clean aircraft. Most airlines choose to maximize aircraft utilization by keeping turnaround times to a minimum. For this reason airlines schedule aircraft in off peak periods with low load factors to maintain frequency share and to position the same aircraft for peak periods of demand. Crew scheduling and routine maintenance requirement must also be considered in the timetable development.(Belobaba et al. 2009)

The fleet assignment process determines which type of aircraft should be used for each departure time. The objective of airline fleet assignment problems is to minimize the combined cost of demand spill and aircraft operating costs. This fleet assignment problem will be further discussed in section 2.4.2 of this dissertation. Once fleet assignment is done aircraft routing and crew assignment models are used to determine specific aircraft for each flight by tail number. (Belobaba et al. 2009) These models address aircraft routine maintenance schedules as well as crew scheduling issues.

### 2.4.2. Modeling Airline Scheduling

Airline schedule optimization is used by airlines to develop future schedules for aircraft and crews. (Belobaba et al. 2009) The objective is to develop profit maximizing schedules that are consistent with operational, marketing, and strategic airline goals. These large optimization problems are typically broken up into sub problems due to the complexity and size of airline operations. The first sub problem is the schedule design problem, where mandatory and optional flight legs are identified for the optimization model. These optional flights can be candidate new flights or current flights under consideration for removal from the schedule. These models typically use a multi-commodity flow network to solve this schedule problem. Flight arcs are used to represent flight legs in the network and ground arcs are used to represent aircraft during the period of examination in the model. Figure 2 shows the fleet-specific time–space network with count time and wrap around ground arcs to represent overnight ground arcs for aircraft.

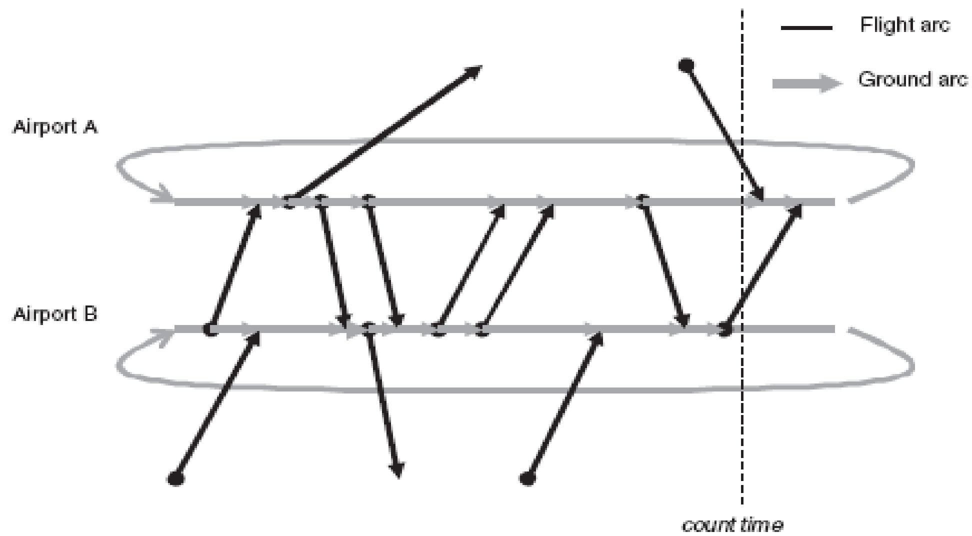



**Figure 2 fleet-specific time–space network with count time and wrap around ground arcs to represent overnight ground arcs for aircraft, from figure 7.5 (Belobaba et al. 2009)**

An example of a final schedule with fleet assignments is shown in Figure 3 below.

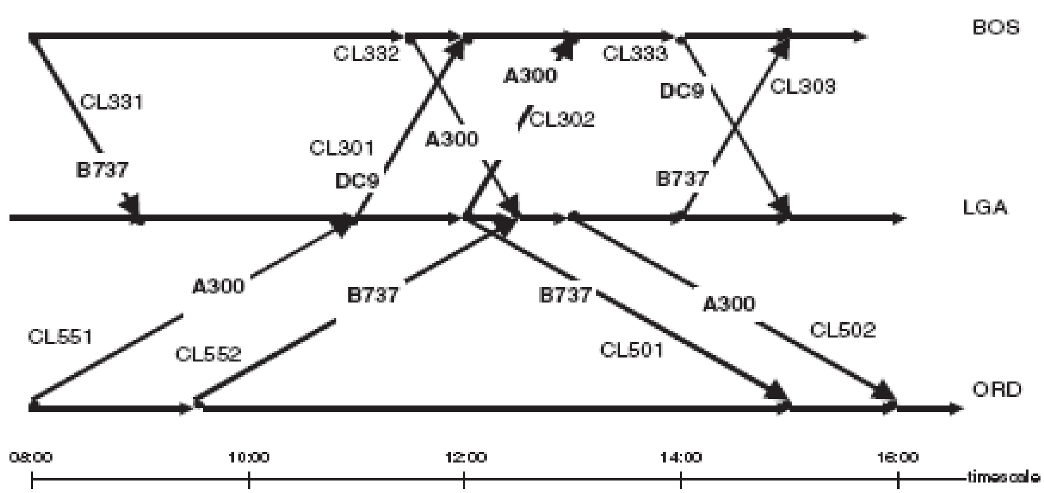



**Figure 3 Optimal fleet assignment example from 7.3 (Belobaba et al. 2009)**

The fleet assignment problem finds a profit-maximizing solution of assigning aircraft types to the flight legs in the airline's network. This is done by matching forecasted passenger demand with aircraft types to minimize operational and demand spill costs for the airline. The last two sub problems match aircraft to specific flight legs while accounting for routine maintenance and matches airline crews to aircraft in the schedule.

## 2.5. Passenger Demand versus Airfare Models

Studies of passenger demand have shown that not only is there a functional relationship between passenger demand and airfare, but there are more factors that come into play. (Richard E. Quandt & William J. Baumol 1966b) (Tretheway & Oum 1992)(Doganis 2002)(Bhadra 2003) Demand is a function of price, the disposable income of the potential travelers, price and convenience of other modes of transport, frequency of service, the timing of the air transportation service, seasonality, safety and quality of this service, the demographics of the connecting markets, distance between these markets, customer loyalty, and travel time. (Tretheway & Oum 1992)

An aviation market is defined when passengers have a propensity to travel between two separate geographic regions. These markets might be serviced by one or more airports for each separate region. (Belobaba et al. 2009a)

Lower airfares induce people to travel more. The following sections will discuss different ways demand is modeled between two markets. The cost of other modes of travel influences passenger demand for commercial air service. On the east coast if it is cheaper to travel by train than by air between two populated areas, then the passenger demand for air service may be decreased. More frequent service represents a more convenient service, thus increasing the customer's willingness to travel by air. Passengers tend to prefer to travel first thing in the morning or late in the afternoon, so adding flights in these time slots of the airline schedule may generate more demand than adding a flight during a non-peak time for demand. Passenger demand is seasonal by month, quarter and by day of week.

Macroeconomic studies examined later in this chapter represent demand as a function of airfare. Gravity models described in the next section derive a single price elasticity curve that generalizes the behavior over several markets; however this dissertation will show that elasticity varies between markets and one needs market-specific elasticity curves for the current research. This dissertation will describe a methodology for obtaining such curves and will show how both the shape and the intercept of such curves change as economic conditions change.

### 2.5.1. Gravity Models

The functional relationship between frequency of flights, timing of flights, cost and other factors (such as seasonality, population density, income, alternative transportation modes) and demand has often been modeled with a gravity equation, shown below:(Quandt & Baumol 1966) The components of this formulation are defined as follows:

T represents the demand between two markets i and j

P is the populations of the respective markets

Y is the incomes for respective markets

M represents a propensity to travel coefficient for one market to another

Nij represents the number of modes serving i and j

Hij represents the travel time between markets and Hijr represents the relative travel time to other modes of travel.

Cij represents the passenger cost of travel between i and j and Cijr represents the relative cost of travel compared to other modes of travel.

Dij represents the departure frequency between markets and Dijr represents the relative departure frequency to other modes of travel.

The coefficients $\alpha$, $\beta$,$\delta$, and $\gamma$ represent the elasticity of demand to that particular factor, or the percentage change in demand from one percent change in the corresponding factor.

$T_{ij} = \alpha_0 P_i^{\alpha 1} P_j^{\alpha 2} Y_i^{\alpha 3} Y_j^{\alpha 4} M_i^{\alpha 5} M_i^{\alpha 6} N_{ij}^{\alpha 7} H_{ij}^{\beta 0} H_{ijr}^{\beta 1} C_{ij}^{\gamma 0} C_{ijr}^{\gamma 1} D_{ij}^{\delta 0} D_{ijr}^{\delta 1}$ (R. E Quandt & W. J Baumol 1966a)

**Equation 2 Gravity demand model, (R. E Quandt & W. J Baumol 1966a)**

Beloboba presents a simpler version of the gravity model where demand on a fixed market with no comparisons to other modes of travel can be examined. (Belobaba et al. 2009) The total trip time represents the total travel time plus time displacement from the desired departure and arrival times. Increases in frequency for markets reduce schedule displacement or wait time between flights for travelers. Thus increased frequency of service on a market reduces this total trip time and increases demand.

Demand = (Market Sizing Parameter) x (Airfare) $^{\text{price elasticity}}$ x (Total Trip Time) $^{\text{time elasticity}}$

**Equation 3 Gravity demand model, (Belobaba et al. 2009)**

These elasticities, especially airfare elasticities allow insight into the differences of different type of travelers. (Tretheway & Oum 1992)(Belobaba et al. 2009a)(Doganis 2002) Belobaba classifies passengers into four categories: (1) The business travelers are time sensitive but relatively insensitive to price. They prefer to travel on flights that meet their schedule and are willing to pay higher fares to do so. (2) The business-leisure travelers are time sensitive and price sensitive. These passengers must travel but they are willing to be flexible to secure a reduced fare. (3) The leisure travelers are willing to change their time and possibly even their day of travel, and event destination airports, to find the lowest possible fare. (4) Lastly there is a rare type of passenger who is insensitive to both price and time constraints, these passengers are willing to pay for high levels of service.

These price and time elasticities can vary by market and type of passenger. In general, inelastic demand is considered to have an elasticity coefficient between 0 and -1. A market's passenger demand with all elasticity coefficients of zero will not change at all regardless of time of travel or airfare changes. Markets with elastic demand have elasticity coefficients less than -1. There exists a saturation point in each market where reductions in airfare or travel time will not increase demand.

The gravity model has been used to find general demand models for aggregated markets. By taking the logarithm of both sides of the gravity formula, the problem becomes a multivariate linear regression problem. The next few paragraphs will provide a description of some of the most cited gravity studies in literature. The following studies attempt to model the variations of cumulative demand between markets as a function of airfare and other market specific variables.

A study of airfares bought over the internet versus traditional non-internet purchased airline tickets found non-internet demand to be less price elastic than on line demand. (Granados et al. 2011)

This study used the gravity demand versus airfare equation as shown in Equation 4 to analyze the impact of the Internet on demand. Specifically this study compared the average price elasticity for 47 U.S. origin-destination city pairs from September 2003 and August 2004 to determine the differences in price elasticity of online versus traditional air travel passengers.

$$Demand = Market\_Cons\tan t * Airfare^{price\_elacticity} * Dis\tan ce^{dis\tan ce\_elacticity}$$

**Equation 4 Gravity Demand versus Airfare Equation**

This analysis derived a general formula for demand to fit all 47 markets. This general formula defines market demand as a function of average market airfare, number of weeks before the flight's departure the ticket was purchased, the type of purchase, whether business or leisure travel, and the city of origin. The study shows how demand changes as a function of average fare and passenger characteristics, but does not to include variables for alternate market behavior.

Bhadra uses the gravity demand model, shown below in the log-log form, to model the US national airspace average daily passenger demand or revenue passenger miles (Pij) for calendar year 2000. The components of the equation are defined as follows:

*i* = origin city; *j* = destination city; *P* = average daily passengers;

*D* and *ND* = dominant airlines and non-dominant airlines; *f* = one-way fare;

*PI* = personal income; Density = population density per square mile;

Interactions = intensity of economic activities as represented by interactions between population and income;

Distance = distance traveled between O&D markets;

Market Power = share of passenger demand by airlines in total O&D market;

Southwest = presence (major or minor presence) of Southwest in the O&D market;

season = adverse spring and summer weather

The hub status of the origin and destination airports as defined by BTS/ USDOT (hub status)

Seasonal effect from air travel in spring and summer (season).

All the coefficients below represent the factor's respective elasticities.

$$
\begin{aligned}
\ln(\mathbf{P_{ij}}) = {} & \alpha + \beta * \ln(f_{ij}) + \chi_i * \ln(PI_i) + \chi_j * \ln(PI_j) \\
& + \delta_i * \ln(Density_i) + \delta_j * \ln(Density_j) \\
& + \phi_i * \ln(Interactions_i) + \phi_j * \ln(Interactions_{ij}) \\
& + \eta * \ln(Market\ Power^{D}{}_{ij}) + \iota * \ln(Market\ Power^{ND}{}_{ij}) \\
& + \kappa^{D} * (Southwest_{\ ij}) + \kappa^{ND} * (Southwest_{\ ij}) \\
& + \gamma_i * (hub\ statusOrigin) + \gamma_j * (hub\ statusDestination) \\
& + \varphi * \ln(Distance_{ij}) + \rho * (season) + \varepsilon_{ij}
\end{aligned}
$$

**Equation 5 Gravity demand model, (Bhadra 2003)**

Bhadra created demand models for 11 different groups based on distance based on 250 mile increments (Table 3), to examine the difference in fare and distance elasticities based on distance groups. The fare elasticities found in this study are shown in Table 4 and the distance elasticities are found in Table 5.

**Table 3 Number of observations and adjusted R2 for 11 different demand models, table 2 from (Bhadra 2003)**

| *Market Hauls (in miles of non-stop distance) (1)* | *N (no. of observations) in the Dataset* | *N (no. of observations) used in Estimation* | *(N in Est / N Data) (%)* | *Adj. $R^2$* | *F-Value* |
|---|---|---|---|---|---|
| <250: Short Haul1 | 2424 | 1785 | 74 | 0.57 | 170.53* |
| 250-499: Short Haul2 | 8161 | 4601 | 56 | 0.51 | 346.92* |
| 500-749: Short Haul3 | 9935 | 5685 | 57 | 0.41 | 287.69* |
| 750-999: Short Haul4 | 8894 | 5396 | 61 | 0.42 | 289.44* |
| 1000-1249: Short Haul5 | 6686 | 3981 | 60 | 0.35 | 155.47* |
| 1250-1499: Medium Haul1 | 4252 | 2457 | 58 | 0.37 | 102.79* |
| 1500-1749: Medium Haul2 | 3239 | 1934 | 60 | 0.50 | 139.35* |
| 1750-1999: Medium Haul3 | 2983 | 1652 | 55 | 0.54 | 141.66* |
| 2000-2249: Long Haul1 | 2184 | 1392 | 64 | 0.55 | 123.54* |
| 2250-2499: Long Haul2 | 2160 | 1310 | 61 | 0.48 | 87.26* |
| 2500-3000: Long Haul3 | 996 | 510 | 51 | 0.48 | 34.24* |
| **Contiguous US NAS Total** | **51914** | **30703** | **59%** | | |

'*': Significant at 99%.

Bhadra's study found average one-way fare in all market segments to be negative and to vary according to the distance of the market. Specifically, passengers in the shorter haul markets were less responsive to changes in fares (i.e. showed inelastic demand). An overall inelastic demand curve, therefore, suggests that travel is perhaps dominated by the business class passengers in the shorter-haul markets.

**Table 4 Fare elasticities by distance group, table 3 from (Bhadra 2003)**

| *Market Hauls (in miles of non-stop distance)* | *Elasticity of Demand with respect to fares* | *t-value* | *Pr > \| t\|* |
|---|---|---|---|
| <250: Short Haul1 | -0.66650 | -11.16 | <.0001 |
| 250-499: Short Haul2 | -0.55762 | -11.32 | <.0001 |
| 500-749: Short Haul3 | -0.73791 | -15.35 | <.0001 |
| 750-999: Short Haul4 | -1.45383 | -28.27 | <.0001 |
| 1000-1249: Short Haul5 | -1.81597 | -29.63 | <.0001 |
| 1250-1499: Medium Haul1 | -0.85086 | -11.55 | <.0001 |
| 1500-1749: Medium Haul2 | -1.07697 | -10.22 | <.0001 |
| 1750-1999: Medium Haul3 | -0.84224 | -8.28 | <.0001 |
| 2000-2249: Long Haul1 | -1.06010 | -9.22 | <.0001 |
| 2250-2499: Long Haul2 | -1.38358 | -9.64 | <.0001 |
| 2500-3000: Long Haul3 | -0.85995 | -3.79 | <.0001 |

**Table 5 Distance elasticities by distance group, table 4 from (Bhadra 2003)**

| *Market Hauls (in miles of non-stop distance)* | *Elasticity of Demand with respect to average distance (miles)* | *t-value* | *Pr > \| t\|* |
|---|---|---|---|
| <250: Short Haul1 | 1.5862 | 20.99 | <.0001 |
| 250-499: Short Haul2 | -0.44612 | -6.16 | <.0001 |
| 500-749: Short Haul3 | -0.16116 | -1.46 | 0.1432 |
| 750-999: Short Haul4 | 0.585804 | 3.56 | <.0004 |
| 1000-1249: Short Haul5 | 0.162264 | 0.61 | 0.5417 |
| 1250-1499: Medium Haul1 | -0.24265 | -0.67 | 0.5054 |
| 1500-1749: Medium Haul2 | 0.052665 | 0.11 | 0.9155 |
| 1750-1999: Medium Haul3 | 0.587395 | 1.08 | 0.2803 |
| 2000-2249: Long Haul1 | 4.070675 | 5.89 | <.0001 |
| 2250-2499: Long Haul2 | 0.491526 | 0.47 | 0.6399 |
| 2500-3000: Long Haul3 | -0.84207 | -0.47 | 0.6391 |

Table 5 shows that average distance may have played a role in passenger demand for only 4 market groups, the significant ones with Pr>|t| < .05. For these 4 market groups (<250, 250-499, 750-999, and 2000-2249), only the 250-499 market showed negative elasticity. Positive distance elasticity indicates demand increases as distance in increased.

Another study used the gravity approach to derive models for passenger demand, revenue passenger miles, and yield per passenger mile for 115 market pairs from 1960 to 1967. (Verleger 1972) This study compares the gravity model for passenger demand to a simple log linear model and to a modified version of the gravity model shown below. The components of the equation are defined as follows:

$T_{ij}$ represents passenger demand, $P_{ij}$ represent the airfare,

*M* represents the collective propensity to travel at the respective markets, or the maximum passengers who would travel from a market with a one dollar airfare.

*X* represents the individual propensity to travel,

*Y* measures the average per capita income,

$\alpha, \beta,$ and $\gamma$ represent the factor's elasticities.

$$T_{ij}(t) = aP_{ij}(t)^{\alpha}M_i(t)^{\beta_1}M_j(t)^{\beta_2}\epsilon,$$

**Equation 6  Gravity demand model, (Verleger 1972)**

$$T_{ij}(t) = \alpha_0 P_{ij}(t)^{\alpha_1}\,\tilde{Y}_{ij}(t)^{\alpha_2}\epsilon,$$

**Equation 7  Simple log linear demand model, (Verleger 1972)**

$$T_{ij}(t) = \alpha_0 P_{ij}(t)^{\alpha_1}\left\{\left(\sum_{K=1}^{N} X_i^K(t)e^{\beta_i \bar{Y}_i^K(t)}\right)\left(\sum_{K=1}^{N} X_j^K(t)e^{\beta_j \bar{Y}_j^K(t)}\right)\right\}^{\gamma}\epsilon$$

**Equation 8  Modified gravity demand model, (Verleger 1972)**

The log linear model fit passenger demand better than the gravity model and the modified gravity model fit the best. The log is taken for both sides of this modified gravity model to enable a linear regression to be done. This study shows that variations in air travel demand between the 115 markets can be explained very well by the incomes of the origin and destination cities.

Another study uses a log linear version of the gravity model to predict passenger demand for markets, as shown below. (Jorge-Calderon 1997) The components of the equation are defined as follows:

*Distance* equals market distance,

*Population* equals the sum of regional populations for the two airports,

*Income* is the average income of the regional populations for the two airports,

*Frequency* of service is the total number of weekly flights for the market,

Average aircraft *Size* is the total number of seats flown divided by the number of flights

*ECONOMY* is the cheapest fare available,

*MODDISC* and *HIDISC* are dummy variables indicating whether moderately discounted fares or highly discounted fares are available,

*PROX* is a dummy variable indicating whether the market is within proximity of a major hum

*SEAX, TOURISM, HUB1*, and *HUB2* are dummy variables that indicate whether the market route flies over sea water, whether the destination is a tourism site, and whether one of the airports (*HUB1*) or both (*HUB2*) were a hub for a major airline.

$\alpha$, $\beta$, and $\gamma$ represent the factor's elasticities.

$$\begin{aligned} \ln TRAFFIC_i = \alpha &+ \beta_1 \ln DISTANCE_i \\ &+ \beta_2 \ln POPULATION_i + \beta_2 INCOME_i \cdots \\ &+ \beta_4 \ln FREQUENCY_i + \beta_5 \ln ASIZE_i \\ &+ \beta_5 \ln ECONOMY_i + \gamma_1 MODDISC_i \, \gamma_2 HIDISC_i \\ &+ \gamma_3 PROX1_i + \gamma_4 PROX2_i + \gamma_5 SEAX_i \\ &+ \gamma_6 TOURISM_i + \gamma_7 HUB1_i + \gamma_8 HUB2_i + \varepsilon) \end{aligned}$$

**Equation 9 Gravity demand model, (Jorge-Calderon 1997)**

Table 6 shows results of fitting three models to the market data. The three different Demand Models are fit models geo-economic variables exclusively (2.1), with all variables (2.2), and with all variables and with *ASIZE* as exogenous variable (2.3). Results show the explanatory power of the regression increases dramatically to reflect 95% of the variation, up from 37%, when service variables are included. Secondly, the service variables assume most of this explanatory power. The loss of significance of many of the geo-economic variables implies that the two sets overlap, and that the absence of one of them would cause the other to absorb some of its effect. For example, larger populations with higher incomes are served by a more frequent service.

**Table 6 Results of three different demand models, 2.1 models geo-economic variables exclusively, 2.2 models all variables, and 2.3 models *ASIZE* as exogenous (Jorge-Calderon 1997)**

| | (2.1) | (2.2) | (2.3) ASIZE exog. |
|---|---|---|---|
| Constant | 0.5063 | 4.7479 | 4.6485 |
| | (0.173) | (7.911)A | (3.150)A |
| Distance | −0.3127 | 0.3066 | 0.4879 |
| | (−2.973)A | (2.544)A | (1.733)B |
| Population | 0.2574 | 0.0188 | 0.0535 |
| | (2.479)A | (0.902) | (0.948) |
| Income | 0.7967 | −0.0908 | −0.0284 |
| | (2.252)A | (−1.385)C | (−0.171) |
| Frequency | | 0.9396 | 0.6506 |
| | | (24.193)A | (3.202)A |
| ASIZE | | 1.1882 | 1.2064 |
| | | (15.390)A | (13.281)A |
| Economy | | −0.5423 | −0.9481 |
| | | (−3.706)A | (−2.115)A |
| MODDISC | | −0.0846 | −0.0654 |
| | | (−2.976)A | (−0.922) |
| HIDISC | | 0.0221 | 0.0045 |
| | | (0.862) | (0.072) |
| PROX1 | −0.4893 | −0.0564 | −0.0451 |
| | (−3.346)A | (−1.845)B | (−0.068) |
| PROX2 | −0.3062 | 0.0624 | 0.1078 |
| | (−0.867) | (0.742) | (0.582) |
| SEAX | 0.3589 | 0.0089 | −0.0899 |
| | (2.944)A | (0.222) | (−0.803) |
| Tourism | | 0.0879 | 0.0482 |
| | | (2.095)A | (0.454) |
| HUB1 | 0.4058 | −0.1257 | −0.1363 |
| | (2.482)A | (−4.225)A | (−1.864)B |
| HUB2 | 1.8650 | −0.1053 | −0.0507 |
| | (8.163)A | (−0.229) | (−0.328) |
| $R^2$ | 0.3709 | 0.9543 | 0.7224 |
| Adj. $R^2$ | 0.3557 | 0.9523 | 0.7104 |
| $F$ (8, 330) | 24.3280 | | |
| $F$ (14, 324) | | 483.2988 | 60.2463 |

Numbers of observations: 339
*T*-ratios in brackets.
A: Significant at 0.05 level on a two-tailed test.
B: Significant at 0.10 level on a two-tailed test.
C: Significant at 0.10 level on a one-tailed test.

The Jorge-Calderon study found demand to be price inelastic to unrestricted economy fares. Price elasticities were found to increase as a function of distance, see Table 7. Service frequency displayed constant elasticity across distance ranges. Aircraft size became more elastic as the market distance increased, resulting in a reversal of the importance of aircraft size and frequency.

**Table 7 Results of three different demand models, with all variables for different market distance groups (Jorge-Calderon 1997)**

| | (3.1) up to 600 km | (3.2) 601–1200 km | (3.3) above 1200 km |
|---|---|---|---|
| Constant | 2.2494 | 8.6595 | 2.8075 |
| | (1.575)C | (5.054)A | (2.077)A |
| Distance | 0.6527 | 0.4974 | –0.1368 |
| | (4.076)A | (1.860)B | (–1.539) |
| Population | 0.0055 | 0.1318 | –0.0251 |
| | (0.106) | (2.057)A | (–0.752) |
| Income | 0.2053 | 0.1318 | 0.0497 |
| | (0.106) | (–2.057)A | (0.563) |
| Frequency | 0.9273 | 0.9520 | 0.9220 |
| | (24.187)A | (26.427)A | (17.505)A |
| ASIZE | 0.7713 | 1.2053 | 1.5344 |
| | (11.588)A | (22.868)A | (6.135)A |
| Economy | –0.7173 | –0.9606 | –0.0234 |
| | (–3.860)A | (–2.088)A | (–0.080) |
| MODDISC | 0.0335 | –0.0019 | –0.0727 |
| | (0.570) | (–0.028) | (–1.200) |
| HIDISC | 0.1472 | 0.1118 | –0.0666 |
| | (2.490)A | (1.743)B | (–1.397)C |
| PROX1 | –0.0926 | 0.0554 | –0.0159 |
| | (–1.603)B | (1.135) | (–0.256) |
| PROX2 | –0.2514 | 0.2824 | |
| | (–1.925)B | (2.017)A | |
| SEAX | 0.1438 | 0.0816 | 0.0159 |
| | (1.640)B | (1.230) | (0.296) |
| Tourism | | –0.1882 | 0.0396 |
| | | (–0.920) | (0.682) |
| HUB1 | 0.0692 | –0.2871 | –0.1052 |
| | (1.369)C | (–3.753)A | (–2.278)A |
| HUB2 | –0.1520 | –0.0773 | –0.0411 |
| | (–1.381)C | (–0.254) | (–0.332) |
| $R^2$ | 0.9892 | 0.9775 | 0.9242 |
| Adj. $R^2$ | 0.9875 | 0.9748 | 0.9137 |
| $F$ (15, 85) | 598.9347 | | |
| $F$ (14, 115) | | 357.7897 | |
| $F$ (13, 94) | | | 88.2166 |

*T*-ratios in brackets.
A: Significant at 0.05 level on a two-tailed test.
B: Significant at 0.10 level on a two-tailed test.
C: Significant at 0.10 level on a one-tailed test.

The Jorge-Calderon study also showed that short haul markets to be relatively price (ECONOMY) insensitive. Therefore lowering airfares for these markets would not generate the demand desired and would only reduce airline revenues.

### 2.5.2. S-Curve Models

In the air transportation industry the S-Curve model is used to represent the interactions between airline frequency share and market share. This model accounts for how competition between airlines affects its market share or percent of demand of the market. The model also captures the effect on airline demand from and incremental increase of frequency of service. (Belobaba et al. 2009)

The S-curve relationship between frequency and market share helps to explain the use by airlines of flight frequency as an important competitive weapon. For example, in a two-airline competitive market, if one airline offers 60% of the non-stop flights it is likely to capture more than 60% of the market share. Conversely, the other airline (with 40% frequency share) will see less than 40% market share. The extent of this disproportionate response of market share to frequency share will depend on the degree to which the S-curve bends away from the market share = frequency share diagonal line. The postulated S-curve makes immediate intuitive sense at three points on Figure 4: (1) when an airline offers zero frequency, it will receive zero market share; (2) at 100% frequency share, it must receive 100% market share; and (3) when both carriers offer 50% of the frequency, they should expect 50% market share, again assuming no significant differences in price or other service factors.

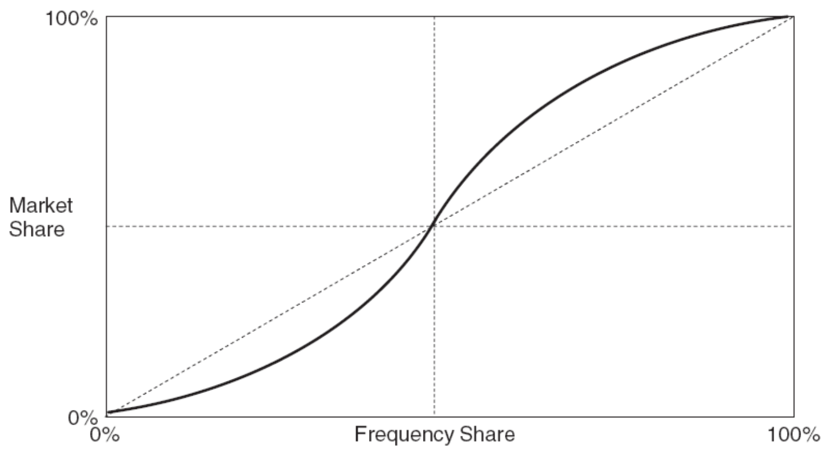



**Figure 4  Market share vs. frequency share S-curve model, figure 3.7 from (Belobaba et al. 2009)**

Button and Drexler examined a number of large carriers for two months (June and October) and two years (1990 and 2004) to determine if there was evidence to support the s-curve relationship between frequency share and market share for airlines. (Button & Drexler 2005)  Limited evidence of this relationship was found in the 1990 data and this relationship had effectively disappeared in the 2004 data.  They suggest that the deregulation of airlines, the emergence of the low cost carriers into air transportation competition, and transparency of airfares on the internet may have reduced the market share impact on ticket sales.

Another study on the impact of aircraft size and seat availability on market share shows negative impacts could be incurred on airlines that choose to up-gauge. (Wei & Hansen 2005)  Figure 5 displays data provided by (Wei and M. Hansen, 2005) that show that increases in capacity through increased service frequency yield approximately equal increases in market share, again the s-curve were not found here. However, increases in capacity through increased aircraft size yield a much smaller increases in market share.

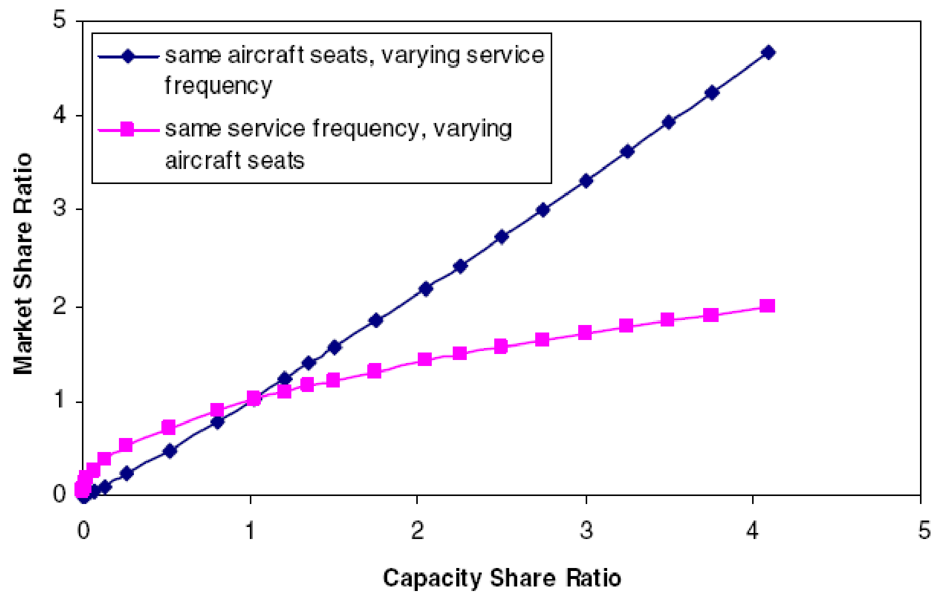



**Figure 5 Changes in market share and capacity share based upon added frequency or aircraft size, figure 2 from (Wei & Hansen 2005)**

## 2.6. Macroeconomic Models used for airline scheduling

The following sections will discuss airline fleet assignment models. It will also present the results of two recent dissertations that studied airline operational behavior in response to economic and airport capacity changes.

### 2.6.1. Airline Fleet Assignment Models (Hane et al. 1995) (Barnhart et al. 2002)(Lohatepanont & Barnhart 2004)(Belobaba et al. 2009)

The following is a fleet assignment problem formulation, often referred to as the basic fleet assignment model or FAM (Hane et al. 1995):

$$\text{Min} \sum_{i \in L} \sum_{k \in K} C_{k,i} f_{k,i} \qquad (1)$$

subject to:

$$\sum_{k \in K} f_{k,i} = 1, \quad \forall i \in L, \qquad (2)$$

$$y_{k,o,t^-} + \sum_{i \in I(k,o,t)} f_{k,i} - y_{k,o,t^+} - \sum_{i \in O(k,o,t)} f_{k,i} = 0, \quad \forall k, o, t, \qquad (3)$$

$$\sum_{o \in A} y_{k,o,t_m} + \sum_{i \in CL(k)} f_{k,i} \leq N_k, \quad \forall k \in K, \qquad (4)$$

$$f_{k,i} \in \{0,1\}, \quad \forall k \in K, \forall i \in L, \qquad (5)$$

$$y_{k,o,t} \geq 0, \quad \forall k, o, t. \qquad (6)$$

**Equation 10 Fleet assignment model formulation, (Hane et al. 1995)**

The objective function is the summation of the operational costs (fuel, gate rental, and take-off and landing), carrying costs (extra fuel, baggage handling, reservation systems processing, and meals), spill costs (revenue spilled from the itineraries due to insufficient capacity), and recaptured revenue (spill costs that are recovered by transporting passengers on itineraries other that their desired itineraries). The coefficient $C_{k,i}$ is the airline costs for aircraft type $k$ and flight leg $i$ and $f_{k,i}$ is a decision variable that indicates whether or not aircraft type $k$ is selected to fly flight leg $i$.

Constraints (2) are cover constraints to ensure each flight leg is covered once by an aircraft type. $M^k$ represents the number of available aircraft of type $k$. Constraints (3) are conservation of flow constraints ensuring aircraft arriving at an airport must eventually depart the airport. $y_{k,o.t_j+}$ is the number of fleet type $k \in K$ aircraft that are on the ground at airport $o \in A$ immediately after time $t_j \in T$. $y_{k,o,t_j-}$ is the number of fleet type $k \in K$ aircraft that are on the ground at airport o ∈ A immediately before time $t_j \in T$. Constraints (4) are count constraints to ensure only available aircraft of type $k$ $(N_k)$ are used in the fleet assignment. In constraint 4, $t(m)$ is a single fixed time when one assures that all aircraft are accounted for, this is usually sometime in the middle of the night (e.g. 3am) when most aircraft are on the ground.

The shortcomings of the FAM are that it assumes demand to be static and known. It assumes that there is an "average" demand over a given season, and that one knows the average airfare for that season. The FAM aggregates demand and averages fares for different fare classes. Without a more accurate representation of demand versus airfare passenger revenues may be misrepresented. In the FAM spill and recapture costs are approximated, assuming the flight legs are unconstrained.

A modified version of the FAM to capture the flow of passengers through the network is called the Itinerary-Based Fleet Assignment Model (IFAM). The formulation is shown below: (Barnhart et al. 2002)

$$\text{Minimize} \quad \sum_{i \in F} \sum_{k \in K} c_i^k f_i^k - \sum_{p \in P} \sum_{r \in P} fare_r b_p^r t_p^r$$

subject to:

$$\sum_{k \in K} f_i^k = 1, \qquad \forall i \in F$$

$$y_{n+}^k + \sum_{i \in O(k,n)} f_i^k - y_{n-}^k - \sum_{i \in I(k,n)} f_i^k = 0, \qquad \forall n \in N^k, \forall k \in K$$

$$\sum_{a \in CG(k)} y_a^k + \sum_{i \in CL(k)} f_i^k \leq M^k, \qquad \forall k \in K$$

$$\sum_{p \in P} \sum_{r \in P} \delta_i^r b_p^r t_p^r \leq \sum_{k \in K} CAP^k f_i, \qquad \forall i \in F \qquad (7.6)$$

$$\sum_{r \in P} t_p^r \leq D_p, \qquad \forall p \in P \qquad (7.7)$$

$$f_i^k \in \{0, 1\}, \qquad \forall i \in F, \forall k \in K$$

$$y_a^k \geq 0, \qquad \forall a \in G^k, \forall k \in K$$

$$t_p^r \geq 0, \qquad \forall p \in P, \forall r \in P \qquad (7.8)$$

**Equation 11 Itinerary-Based Fleet Assignment Model (IFAM) formulation, (Barnhart et al. 2002)**

The IFAM subtracts the anticipated revenues from captured spilled passengers in the objective function. Where $fare_r$ is the average fare for recaptured passengers, $b^r_p$ is the estimated passengers spilled from itinerary *p* that are recaptured on itinerary *r*, and $b^r_p$ are the number of passengers desiring to travel itinerary p that are spilled on itinerary *r*.

New constraints (7.6) limit the total number of passengers assigned to itinerary *p* to the total available seats. New constraints (7.7) limit the total number of passengers spilled from itinerary *r* to itinerary *p* to the total unrestricted demand for itinerary *p*, $D_p$.

The IFAM solution approach is shown in Figure 6. The process starts off by constructing a restricted master problem (RMP) excluding constraints limiting spilled demand (7.7) and spill variables. The LP relaxation of the RMP is solved using column and row generation. Reduced costs and cuts are added to the RMP and this process is repeated unit the IFAM LP relaxation is solved. Given the IFAM LP solution, branch and bound is invoked to determine an integer solution.

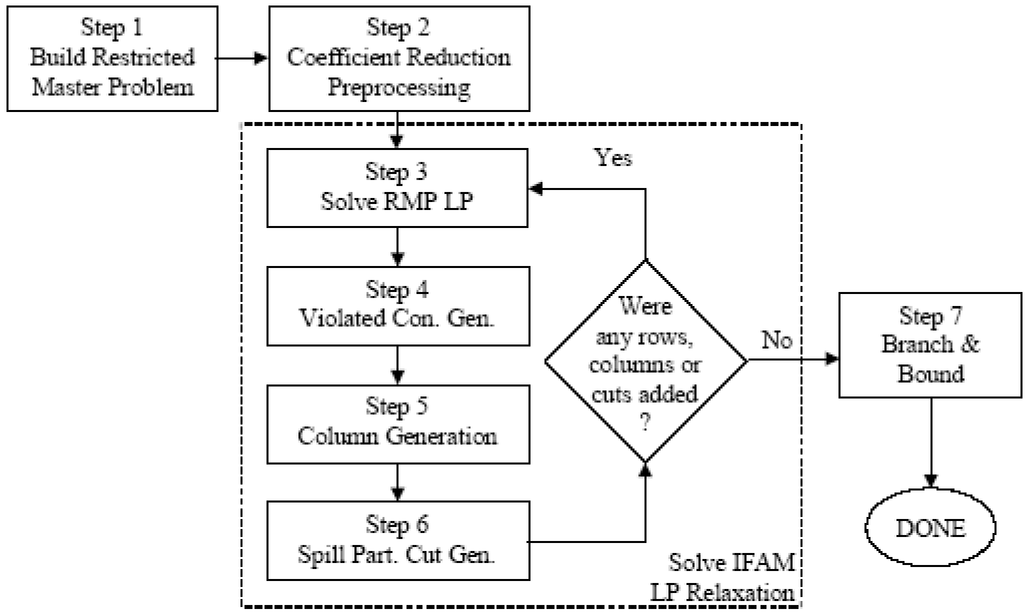



**Figure 6  the IFAM Iterative solution approach, Figure 1 from (Barnhart et al. 2002)**

The IFAM was improved to account for market share or passenger demand adjustments based upon changes in service frequency for markets. The new model is called the integrated schedule design and fleet assignment model (ISD-FAM). The formulation of the ISD-FAM is shown below: (Lohatepanont & Barnhart 2004)

$$\text{Min} \sum_{i \in L} \sum_{k \in K} C_{k,i} f_{k,i} + \sum_{p \in P} \sum_{r \in P} (\widetilde{fare}_p - b_p^r \, \widetilde{fare}_r) t_p^r$$

$$+ \sum_{q \in P^O} \left( \widetilde{fare}_q D_q - \sum_{p \in P: p \neq q} \widetilde{fare}_p \; \Delta D_q^p \right) \cdot (1 - Z_q) \qquad (8)$$

subject to

$$\sum_{k \in K} f_{k,i} = 1 \quad \forall i \in L^F, \qquad (9)$$

$$\sum_{k \in K} f_{k,i} \leq 1 \quad \forall i \in L^O, \qquad (10)$$

$$y_{k,o,t^-} + \sum_{i \in I(k,o,t)} f_{k,i} - y_{k,o,t^+} - \sum_{i \in O(k,o,t)} f_{k,i} = 0$$

$$\forall \{k, o, t\} \in N, \qquad (11)$$

$$\sum_{o \in A} y_{k,o,t_n} + \sum_{i \in CL(k)} f_{k,i} \leq N_k \quad \forall k \in K, \qquad (12)$$

$$\sum_{p \in P} \sum_{q \in P^O} \delta_i^p \Delta D_q^p (1 - Z_q) + \sum_{k \in K} CAP^k f_{k,i} + \sum_{r \in P} \sum_{p \in P} \delta_i^p t_p^r$$

$$- \sum_{r \in P} \sum_{p \in P} \delta_i^p b_r^p t_r^p \geq Q_i \quad \forall i \in L, \qquad (13)$$

$$\sum_{q \in P^O} \Delta D_q^p (1 - Z_q) + \sum_{r \in P} t_p^r \leq D_p \quad \forall p \in P, \qquad (14)$$

$$Z_q - \sum_{k \in K} f_{k,i} \leq 0 \quad \forall i \in L(q), \qquad (15)$$

$$Z_q - \sum_{i \in L(q)} \sum_{k \in K} f_{k,i} \geq 1 - N_q \quad \forall q \in P^O, \qquad (16)$$

$$f_{k,i} \in \{0, 1\} \quad \forall k \in K, \forall i \in L, \qquad (17)$$

$$Z_q \in \{0, 1\} \quad \forall q \in P^O, \qquad (18)$$

$$y_{k,o,t} \geq 0 \quad \forall \{k, o, t\} \in N, \qquad (19)$$

$$t_p^r \geq 0 \quad \forall p, r \in P. \qquad (20)$$

**Equation 12 integrated schedule design and fleet assignment model (ISD-FAM) formulation, (Lohatepanont & Barnhart 2004)**

Constraints 13 through 16 are modified to account for demand adjustment based on changes in the schedule. The ISD-FAM applies similar solution methods as explained above for the IFAM.

Methodologies found in the airline FAMs are leveraged for the solutions of this dissertations problem. The FAM models take a schedule and market demand forecasts from the airline marketing department and assigns the optimal fleet mix to this schedule. Although our modeling approach is similar in that it also uses column-generation and fleet-assignment sub models, it does not assume the schedule in advance but rather works to find profitable schedules as columns to be used in the master problem.

### 2.6.2. Simulating Airline Operational Responses to Environmental and Capacity Constraints (Evans, Antony 2010)(Evans & Schäfer 2011)

These studies describe a macroeconomic model called an airline response model. This model examines changes in airline flight frequencies, aircraft size, and flight network in response to airport capacity constraints within a competitive environment. This approach uses a one-stage Nash best-response game to simulate the profit-maximizing behavior of the airlines being modeled. This model uses airline aggregate market characteristics as inputs to the model, such as segment flight frequency by aircraft type, total itinerary demand, average operating costs per hour by aircraft type, average airfares by market, and average service costs per passenger.

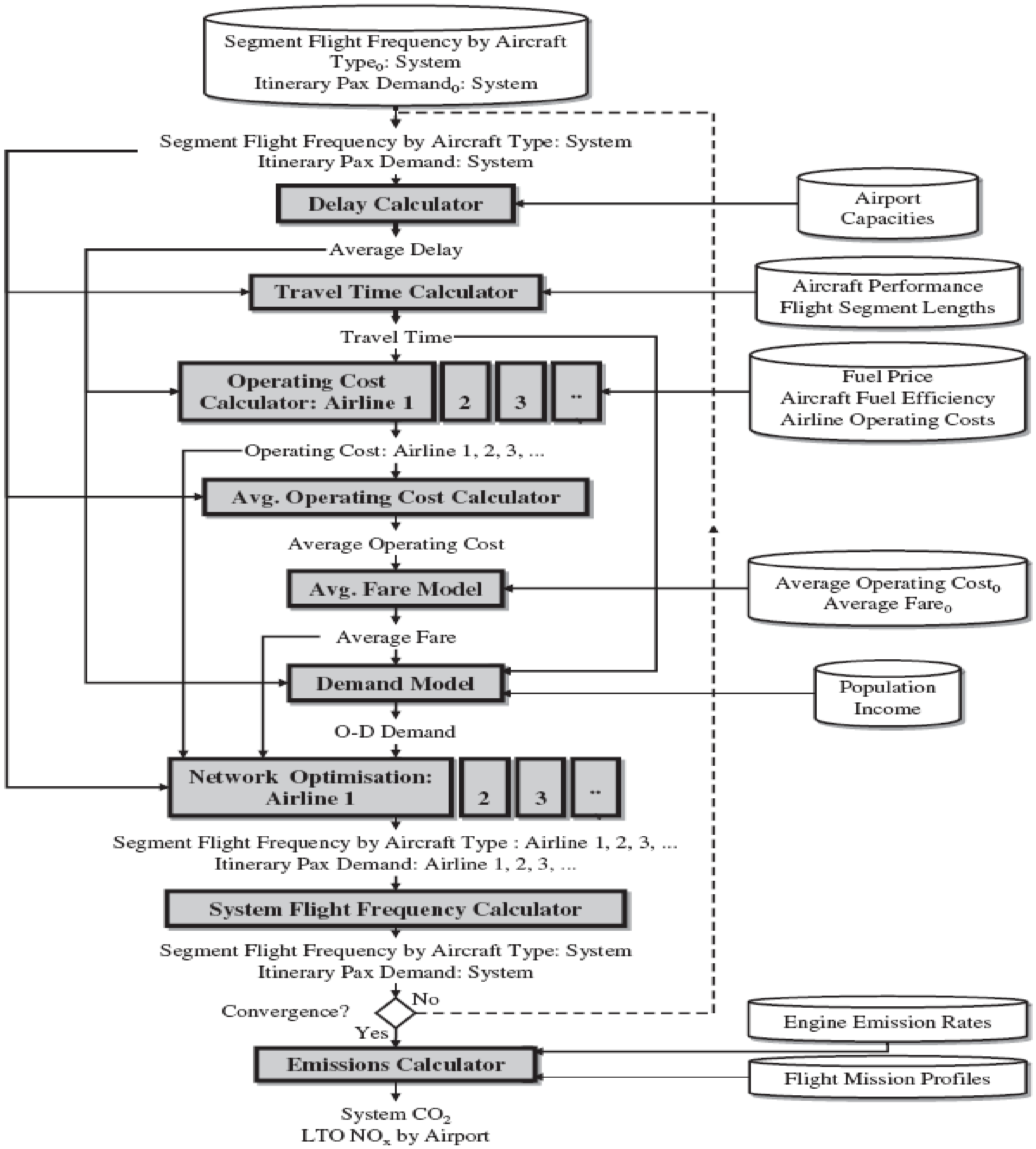



**Figure 7 Evan's airline response model, from figure 1 in (Evans & Schäfer 2011)**

Evan's airline response model as, shown in Figure 7 above, starts by calculating average flight delays by airline and market, based upon a stochastic queuing delay model. Evans calls this module of his model the Delay calculator, which takes as an input the airlines initial desired schedule as the demand versus capacities of the airports derived from the FAA Aviation System Performance Metrics (ASPM) database. Average travel times are also calculated from the ASPM database by airline, market and aircraft type.

Direct operating costs and aircraft servicing costs are calculated for three aircraft classes (small (up to 189 seats/ operation), medium (between 190 and 300 seats/ operation), and large (over 301 seats/ operation)) using the BTS P52 database. Fuel costs are calculated separately using fuel prices from Air Transportation Association (ATA) data and are assumed to change over time based on the oil price forecasts from the MIT integrated global systems model (IGSM). Fuel burn rates are estimated using the EUROCONTROL Base of Aircraft Data (BADA). With this data each airlines costs are calculated for each individual flight from the current models schedule. These costs are then averaged to determine average flight costs by airline, class of aircraft, and market. Also average service costs per passenger are calculated by airline. Costs are based on unimpeded travel times and delay estimates from the earlier delay calculator.

Next the Airline Response Model proportionally adjusts initial average airfares for the markets for each airline proportionally to the change in initial average operating costs. These new average market airfares (*Fare*) along with market populations (*P*), market per capita income (*I*), previously calculated trip travel time (*T*), and delay are plugged into the gravity model shown below to calculate new market demands. The elasticities used in the gravity model are shown in Table 8 and are used for all markets.

$$D_{ij} = (P_i P_j)^{\alpha} (I_i I_j)^{\gamma} e^{\delta A_{ij}} e^{\varepsilon B_{ij}} e^{\phi S_{ij}} \left(\overline{Fare}_{i,j} + \theta_1 \cdot \overline{T}_{i,j} + \theta_2 \cdot \overline{Delay}_{i,j}\right)^{\tau}$$

**Equation 13 Gravity demand model with integrated delay costs, (Evans, Antony 2010)**

**Table 8 Gravity demand model estimated elasticities for market factors, from table 5-2 (Evans, Antony 2010)**

| Population (α/2) | Income (γ/2) | Special Parameter 1 (δ) | Special Parameter 2 (ε) | Special Parameter 3 (φ) | Generalised Cost (τ) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|
| 0.79<br>(0.087) | 0.65<br>(0.143) | 0.46<br>(0.067) | -0.53<br>(0.079) | -3.81<br>(0.183) | -1.04<br>(0.093) | 0.85 |

Next the Airline Response Model uses multi-commodity mixed integer programming to optimally change the individual airline schedules by no more than one flight per day per market. This network optimization module maximizes the profit of the airline subject to the passengers on the scheduled flights being less than or equal to the frequency share of the airline for the market times the market's demand. The airline schedule for each market can only be changed by one flight from the current schedule. The load factors for the scheduled flights cannot exceed 95%. Network flow constraints require flight arrivals to equal departures by aircraft type and market. And, the model requires that all scheduled flight frequencies are non-negative integers.

The airline game is simulated by updating the flight frequencies offered by all airlines according to the outputs of each airline's network optimization. These flight frequencies are inputs to the market share formulation within the demand constraint in each network optimization, the S-Curve, which drives the gaming effect. Thereby, each airline may increase or decrease its frequency in order to capture more market share. Each airline stops increasing frequency as soon as the marginal cost of adding a flight is greater than the marginal revenue obtained from the increased market share gained by adding the flight. Since airlines experience different operating costs, those with the lowest costs can add more extra flights and thus gain more market share. The system reaches the game-theoretical equilibrium when all airlines reach equilibrium on all markets.

The model is validated by reproducing historical passenger flows and flight frequencies for a network of 22 airports serving 14 of the largest cities in the United States, using 2005 population, per capita income and airport capacities as inputs. The estimated passenger flows and flight frequencies compare well to observed data for the same network (the $R^2$ value comparing flight segment frequencies is 0.62). After validation, the model is applied to simulate traffic growth and carbon dioxide and nitrogen oxide emissions within the same network from 2005 to 2030 under a series of scenarios.

These scenarios investigate airline responses to (i) airport capacity constraints, (ii) regional increases in costs in the form of landing fees, and (iii) major reductions in aircraft fuel burn, as would be achieved through the introduction of radically new technology such as a blended wing body aircraft or advanced open rotor engines.

The simulation results indicate that, while airport capacity constraints may have significant system-wide effects, they are the result of local airport effects which are much greater. In particular, airport capacity constraints can have a significant impact on flight delays, passenger demand, aircraft operations, and emissions, especially at congested hub airports. If capacity is available at other airports, capacity constraints may also induce changes in the flight network, including changes in the distribution of connecting traffic between hubs and the distribution of true origin-ultimate destination traffic between airports in multi-airport systems. Airport capacity constraints are less likely to induce any significant increase in the size of aircraft operated, however, because of frequency competition effects, which maintain high flight frequencies despite reductions in demand in response to increased flight delays. The simulation results also indicate that, if sufficiently large, regional increases in landing fees may induce significant reductions in aircraft operations by increasing average aircraft size and inducing a shift in connecting traffic away from the region. The simulation results also indicate that the introduction of radically new technology that reduces aircraft fuel burn may have only limited impact on reducing system $CO_2$ emissions, and only in the case where the new technology can be taken up by the majority of the fleet. The reason for this is that the reduced operating costs of the new technology may result in an increase in frequency competition and thus aircraft operations. In conclusion, the modeling of airline operational responses to environmental constraints is important when studying both the system and local effects of environmental policy measures, because it captures the capability of the air transport system to adjust under changing conditions.

#### 2.6.3. Demand Management at congested airports: How far are we from utopia? (L. T. Le 2006)(L. Le et al. 2008)

Le developed an aggregate airline scheduling model to examine how flight schedules might change if airlines had to restrict their schedules to be consistent with runway capacity. She modeled a profit-seeking, single benevolent airline, and developed an airline economic model to simulate airline scheduling decisions. This airline is benevolent in the sense that it considers historic pricing at LaGuardia and the associated price-elasticity and attempts to service this population while simultaneously remaining profitable. She incorporated the relationship between supply and demand through price elasticity, which she estimated through BTS itinerary and fare data.

The flight schedules were determined through the interaction of two processes or models: (i) airlines seek profit-maximizing schedules and (ii) airports maximize enplanement opportunities subject to capacity constraints. The former is called the “sub-problem”, and the latter is referred to as the “master problem”. In the sub-problems, airlines were modeled aggregately as a single benevolent airline seeking flight schedules for individual markets. The aggregate airline is benevolent in the sense that it reacts to actual price elasticities of demand estimated in a competitive market. Unlike other airline flight scheduling models that use fare as a parameter, Le's airline model explicitly accounts for the interaction of demand and supply through price. The airport model in the master problem solves a set packing problem to select the most efficient market schedules. The solution methodology for solving the overall problem is a Dantzig-Wolfe decomposition, where the columns within the master-problem are schedules that are generated based on an announced dual-price vector. As new schedules are presented, the master problem is solved, thereby generating a new dual-price vector. The process continues until equilibrium is reached, i.e. no new schedules are found that can improve the profitability of the master problem.

Le found that at Instrument Meteorological Conditions (IMC) runway rates, the market can find profitable flight schedules that reduce substantially the average flight delay while accommodating the current passenger demand at prices consistent with the current competitive market. The IMC rate provided a predictable on-time performance for the identified schedules in all weather conditions. In addition, the reduction of flights through consolidation of low load-factor flights and through aircraft up-gauging alleviated much of the current traffic pressure on high-demand airports.

## 2.7. This dissertation's relationship to the literature

This dissertation examines elasticities similar to Le's method described above and obtains a unique elasticity curve for each market served by a given airport. In this way, one can consider the competition among markets and the relative reaction to changes in price or schedule at a specific market.

These curves are then expanded to consider how their shape and/or intercept may change with changes in economic conditions. Finally, these elasticity curves are embedded in an equilibrium model similar to that developed by Le (2006). The model has been changed to consider the impact that international travel has on demand for the domestic portion of the entire international trip, broadens the types of aircraft that can be employed by a given flight, and improves on the efficiency of the Danzig-Wolfe decomposition methodology.

This equilibrium model is first used with historical data as a validity check and then applied to answer the following questions:

1. How does reduced capacity limits imposed at congested airports affect geographic access, economic access, profitability, and the efficiency of the United States air transportation system?

2. How do increases or reductions in aviation fuel price affect geographic access, economic access, profitability, and the efficiency of the United States air transportation system?

## 2.8. Contributions

The studies presented in this chapter are essential building blocks to understanding and solving the problems for this dissertation, however the questions asked in this dissertation could not be answered with the macroeconomic models presented in this chapter as shown in Table 9. The inability of these models to account for international passengers and flights when adjusting airport capacities provided an opportunity for contribution to the study of designing optimal airline schedules. Additionally, the lack of capability to change individual market price versus demand curves based upon changes in aviation fuel prices provided another opportunity for contribution to the study of designing optimal airline schedules. Table 1Table 9 illustrates the capabilities of each of the individual components that were combined in the research of this dissertation.

**Table 9 Daily airport schedule model's functional requirements versus available approaches**

| Develop Airport Daily Schedule | | Barnhardt et al. (2004) | Evans (2010) | Le (2006) | Contribution: Ferguson |
|---|---|---|---|---|---|
| Required | Required Functionality | FAM Models | Airline Response Model | Benevolent Monopolistic Airline | Airport Schedule Optimization Model (ASOM) |
| Optimal Fare and Schedule Selection | Maximize airline profits | ✓ | ✓ | ✓ | ✓ |
| | Optimal Fleet Assignment | ✓ | ✓ | ✓ | ✓ |
| | Demand Adjustments based on Airfare | | ✓ | ✓ | ✓ |
| | Individual Market Demand vs Airfare (Optimal Airfare) | | | ✓ | ✓ |
| Adjust Airport Capacities | TOD Modeled Demand | | | ✓ | ✓ |
| | International Flights | | | | ✓ |
| | International Passengers | | | | ✓ |
| Adjust Airline Fuel Prices | Demand versus Airfare Response | | | | ✓ |
| | Airfare Response | | ✓ | | ✓ |

The methodology of modifying Le's model for these added capabilities are discussed in the following two chapters.

# CHAPTER 3 – DOMESTIC PASSENGER DEMAND BEHAVIOR ANALYSIS IN RESPONSE TO ECONOMIC FLUCTUATIONS IN FUEL PRICES AND NATIONAL UNEMPLOYMENT RATES

This chapter will discuss the challenges of modeling economic fluctuations within an airline macroeconomic model. More specifically the challenge of capturing the effects of economic fluctuations on passenger demand versus airfare curves, so that airline scheduling models can choose correct airfares and schedules to maximize profits. At issue here is the fact that during economic downturns, passenger behavior changes. Specifically, even if airfares and flight schedules remained constant, less people would choose to fly. Airlines understand this phenomenon and also reduce their overall schedule. Therefore the following analysis was conducted to enable the Airport Schedule Optimization Model (ASOM) to reflect shifts in either the shape or the intercept of the passenger demand versus airfare market functions for different economic conditions. To develop a passenger behavior model to complement the ASOM discussed in chapter 4, the following issues must be addressed:

- Which is the best methodology to model passenger demand versus airfares?

- Which is the best methodology to capture economic fluctuations in airline macroeconomic models? How can this process be validated?
- What is the best strategy for prorating itinerary airfares to flight segments?

## 3.1. Modeling Passenger Demand versus Airfare

In chapter 2, two methodologies of modeling passenger demand were introduced; the S-curve or logit model and the gravity model. The following sections will summarize the differences between these models and the exponential passenger demand model and will evaluate the pros and cons of each approach.

### 3.1.1. Different approaches to modeling passenger demand versus airfare behavior

In order to analyze economic impacts on passenger demand versus airfare curves the data must first be fit into a general model. In order to do this an examination of different ways to model passenger must be conducted. The following is a summary of the different approaches to modeling passenger demand versus airfare, for more information on this subject please refer to chapter 2 of this dissertation.

(Oum et al. 1992)(Button 1999) (Brueckner 2004) provide a good foundation of understanding passenger demand and the primary factors which influence this demand.

Logit models have also been used to represent passenger demand as it changes with frequency share and market share between airlines. (Dresner et al. 2002), (Button &

Drexler 2005) These models are not appropriate to analyze passenger demand changes in response to changes in airfares. These models also model the effects of competition between airlines which is not appropriate for a macroeconomic model of a single aggregate airline.

Over the past couple of decades many different approaches have been used to derive a general demand for aviation networks which model to describe how demand changes as a function of airfare, total trip time or distance, economic factors, population, available disposable income, competition, etc. This approach has typically been approached by using regression to define a multiplicative model's coefficients or a gravity equation, see example below. (Quandt & Baumol 1966)(Belobaba et al. 2009)

$$Passenger\ Demand =$$
$$Market\ Demand * avg\ airfare^{price\ elasticity} * total\ trip\ time^{time\ elasticity}$$

The gravity model, which is used predominately in the air transportation industry, develops a network model explaining the differences between various market demands as a function of average market airfare, market distance or travel time, market population, market average per capita income, and other market specific factors. These gravity models are then used to determine changes in individual market demand from changes in airfares or other factors captured in the model.

In this model, the price elasticity represents the change in percentage of passenger demand in response to one percent change in average airfare. Likewise, the time elasticity represents the change in percentage of passenger demand in response to one percent change in total trip time. Belobaba and others using travel trip time are typically using proprietary data for this measure. However, travel time is highly correlated with distance and distance is publically available, so distance elasticities can also be determined for the markets under examination.

This gravity equation has been modified several times to try to develop a more general formula to capture airline competition factors, airline efficiency or delay factors, and other factors to capture the differences in demand between markets.(Bhadra 2003)(Grosche et al. 2007)(Jorge-Calderon 1997)

Further analysis of demand has been conducted to understand the effect of internet ticket sales and airline technology investments.(Kauffman & Weill 1989)(Granados et al. 2011) Additional analysis has been done using the gravity model on the price elasticities for tourism and the factors which change these elasticities.(Morley 1998)

Another method of modeling passenger demand versus airfare is by using a semi-log or exponential formulation, as shown below. (Le 2006)

$$Passenger\ Demand = Market\ Demand * exp^{-price\ coef*avg\ airfare}$$

This exponential model for passenger demand versus airfare assumes a constant decay that is estimated by a price coefficient (represented here as price coef), where the inverse of the price coefficient indicates the airfare change that would either double/halve the passenger demand if the airfare was reduced/increased by this amount respectively.  This model approach models individual market demand responses to changes in airfares.

In summary the logit or s-curve approach does not explain demand versus airfare relationships for individual markets, the gravity approach develops a general model of demand for a network of aviation markets, and the exponential approach develops individual market models to represent demand versus airfare.

### 3.1.2. Study Questions

To determine whether a general market model for demand versus airfare or a collection of individual market models are appropriate, the following questions need to be examined.

Are elasticities constant over time?  Are elasticities different for different markets?  Are elasticities different within market groups?  Do price elasticities change in response to changes in economic factors (fuel prices and unemployment rates)?

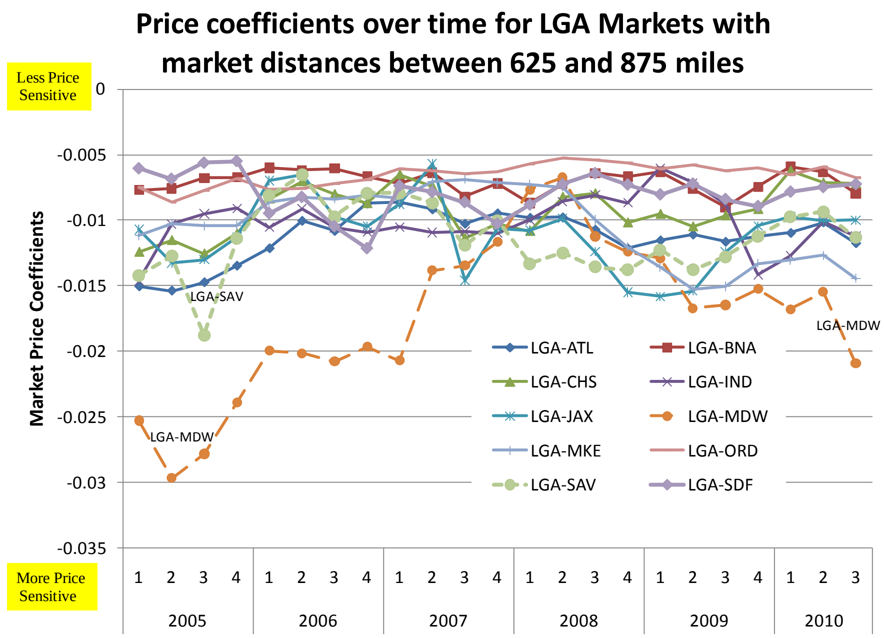



**Figure 8 Exponential Price coefficients over time for LGA markets with market distances between 625 and 875 miles**

Figure 8 shows analysis of individual market price coefficients for LGA markets served between 625 and 875 miles from LGA. These samples of markets are representative of all markets analyzed in this study. Very few markets show no variation in their price coefficients over time, even when serving markets in the same distance bands as shown in Figure 8. This analysis shows that market price coefficients vary over time and between markets, so a model is needed to represent this variation. The LGA-MDW market shows a different type of variation, but this behavior is the exception not the norm.

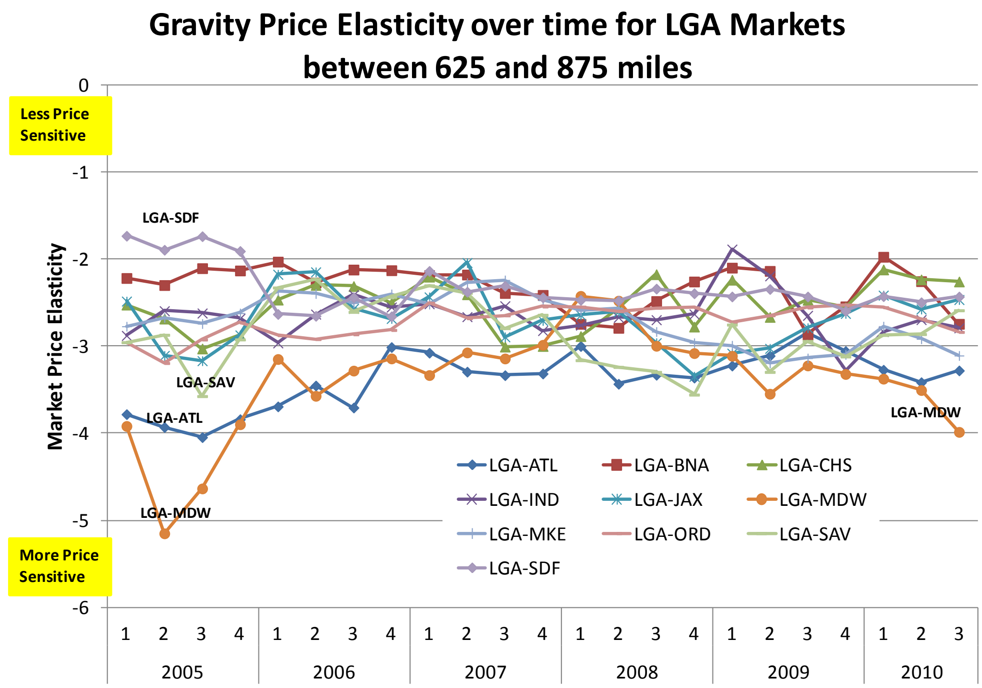



**Figure 9 Exponential Price coefficients over time for LGA markets with market distances between 625 and 875 miles**

Figure 9 shows analysis of individual market price elasticities for LGA markets served between 625 and 875 miles from LGA. These samples of markets are representative of all markets analyzed in this study. Very few markets show no variation in their price elasticity over time, even when serving markets in the same distance bands as shown in Figure 9. This analysis shows that market price elasticity varies over time and between markets, so a model is needed to represent this variation. The LGA-MDW market shows a different type of variation, but this behavior is the exception not the norm.

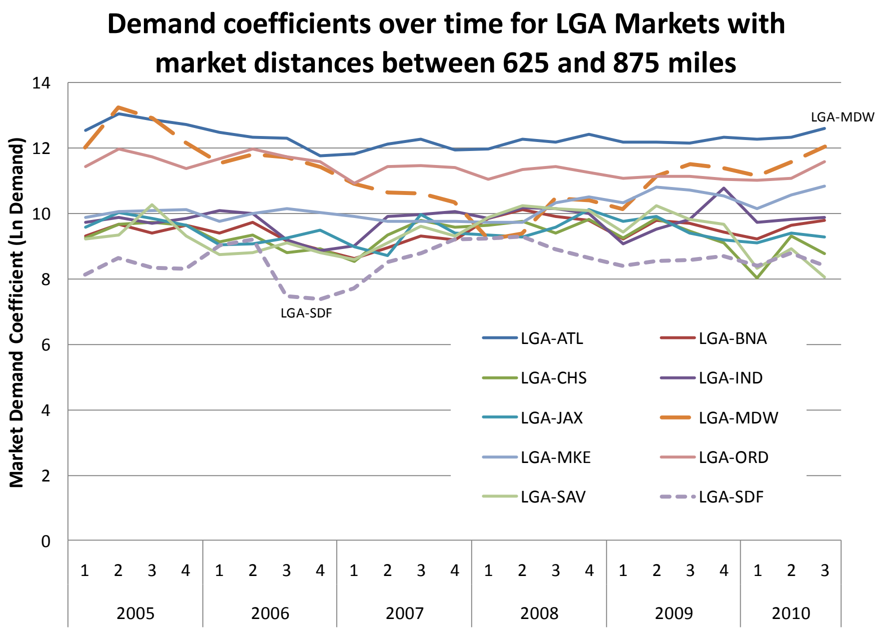



**Figure 10 Exponential Demand coefficients over time for LGA markets with market distances between 625 and 875 miles**

Figure 10 shows analysis of individual market exponential demand coefficients for LGA markets served between 625 and 875 miles from LGA. These samples of markets are representative of all markets analyzed in this study. Very few markets show no variation in their demand coefficients over time, even when serving markets in the same distance bands as shown in Figure 10. This analysis shows that market demand coefficients vary over time and between markets, so a model is needed to represent this variation.

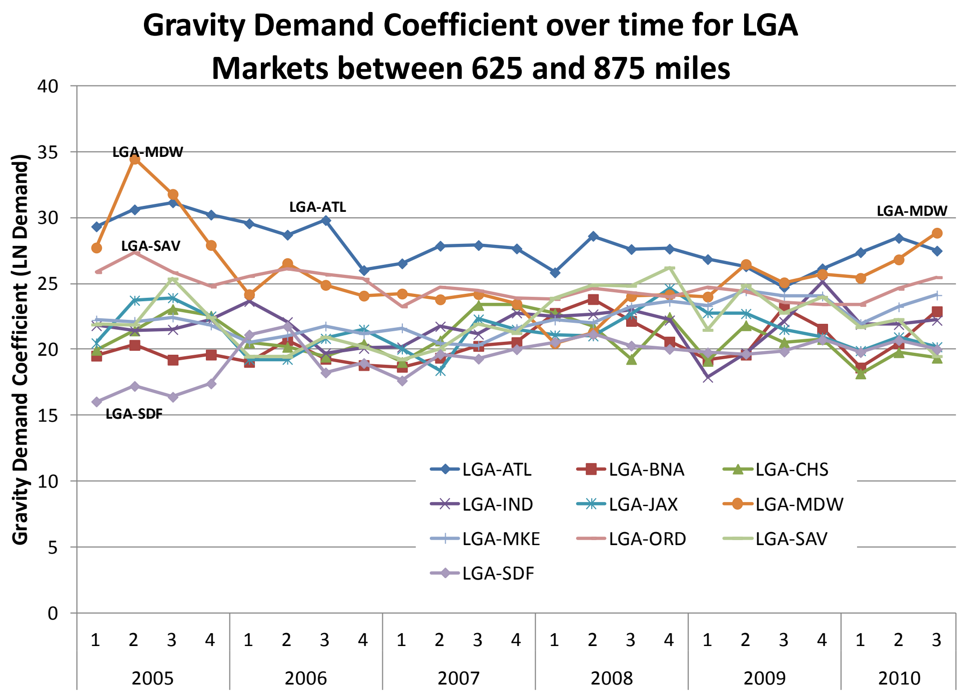



**Figure 11 Gravity Demand coefficients over time for LGA markets with market distances between 625 and 875 miles**

Figure 11 shows analysis of individual market gravity demand coefficients for LGA markets served between 625 and 875 miles from LGA. These samples of markets are representative of all markets analyzed in this study. Very few markets show no variation in their demand coefficients over time, even when serving markets in the same distance bands as shown in Figure 11. This analysis shows that market demand coefficients vary over time and between markets, so a model is needed to represent this variation.

This analysis suggests that it will be difficult to develop a general model which accurately captures most of these differences. An alternative is to model each market individually thereby capturing the unique characteristics of the market with the impacts from seasonality and the economy. Therefore to more accurately reflect market demand versus airfare relationships for the ASOM, the approach of developing individual market demand versus airfare models will be used.

For the purposes of this analysis a model to represent individual markets will be required to examine the effects of economic factors on the coefficients of demand and price elasticity. Therefore the gravity and exponential models will be examined to determine the best fits, see section 3.2.4.

## 3.2. Preprocessing Revenue versus Demand curves

Data representing passenger behavior of demand versus airfares can be found in the Bureau of Transportation Statistics (BTS) Airline Origin and Destination Survey (DB1B) database. (U.S. DOT /BTS 2010) The DB1B database is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the Bureau of Transportation Statistics. Data includes origin, destination and other itinerary details of passengers transported. This database is used to determine air traffic patterns, air carrier market shares and passenger flows. For this particular analysis this database will be used to determine passenger behavior in the form of passenger demand versus average airfares.

The DB1B market database contains directional market characteristics of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators. Round trip itineraries are split in two for this database. This database contains direct itineraries and connecting itineraries, as shown in the number of segments in the itineraries in Table 10. In order to evaluate passenger demand for non-stop direct domestic markets or segments the airfares for these connecting itineraries (more than one segment) must be further prorated down to the segments of interest.

**Table 10 Airline Origin and Destination Survey (DB1B) "Market" database**

| Year | Qtr | number of segments | # of Itineraries | % of Itineraries | # of Pax | % of Pax |
|---|---|---|---|---|---|---|
| 2007 | 3 | 1 | 2,041,131 | 39% | 7,973,245 | 67% |
| 2007 | 3 | 2 | 2,916,989 | 55% | 3,580,773 | 30% |
| 2007 | 3 | 3 | 266,179 | 5% | 274,450 | 2% |
| 2007 | 3 | 4 or more | 31,684 | 1% | 32,235 | 0.3% |

### 3.2.1. Calculating proportional fares for passenger trip segments

Discussions with the BTS DB1B database administrators revealed there are two traditional approaches in prorating segment fares from an itinerary fare. The first method is called the Yield approach, because the segments airfare is generated from an average yield or revenue per passenger mile. For example, an itinerary with revenue $400 for 400 miles has a yield of $1 per passenger mile. And a proration of this revenue for a 200 mile segment would be $1 per passenger mile times 200 miles, or $200 per passenger. This approach is used to split the fare for round trip itineraries into the DB1B market itineraries. This approach is the simplest, but is not accurate for itineraries where the segments vary significantly are length.

A second method prorates the airfares based upon actual direct single segment fares. In this approach, one extracts the single direct non-stop segment fares for all of the segments of the itinerary and applies the proportion of the whole itinerary airfare equal to the proportion of the segments direct non-stop segment airfare over all single direct non-stop segment fares for all of the segments of the itinerary. For example, an itinerary with revenue $400 for 400 miles has two segments of 100 and 300 miles respectively. The direct non-stop segment airfares for these segments were $150 and $350 respectively. Then this method would apply 30% ($150/ ($150+$350)) of the $400 for the itinerary airfare or $120 for the 100 mile segment and the remaining $280 for the 300 mile segment. While this approach is considered the best approach for prorating it is also very complex and not all segments flown have non-stop segment airfares, so approximation methods have been developed to represent this method.

American Airlines applies an approximation method which prorates airfare based on the square root of the segment distance divided by the sum of the segment distance square roots (Le 2006). GRA, Inc. uses an approximation method which prorates airfare based on the .74 power of the segment distance divided by the sum of the .74 power of all itinerary segment distances. Analysis of DB1B data showed that segment distance to the .4166 power divided by the sum of the .4166 power of all itinerary segment distances was the best fit to approximate method two above. However, prorating based on the square root of the segment distance performs nearly as well, as shown in Figure 12.

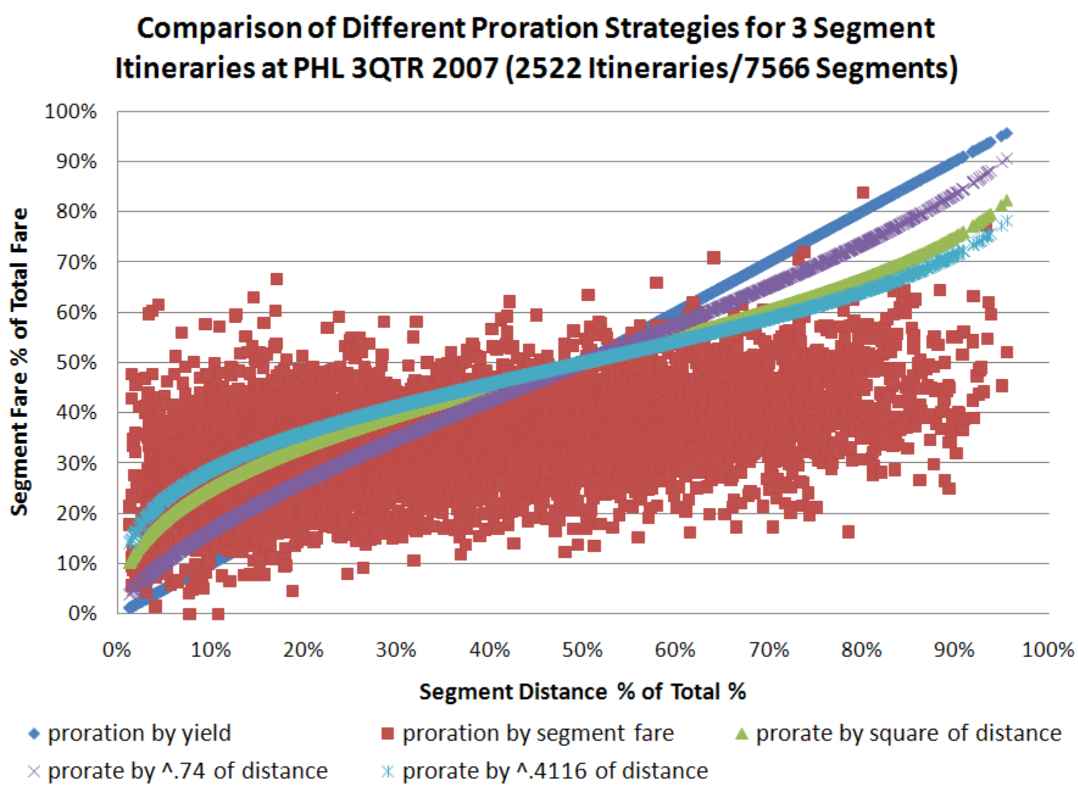



**Figure 12 Comparison of different proration approximation techniques for 3 segment itineraries**

Figure 12 shows an analysis of 2522 Itineraries for PHL airport third quarter 2007. Each of these itineraries had three flight segments which could individually be analyzed in the BTS DB1B database for average fares. Therefore, with this data a comparative analysis is shown between the different approximating techniques to proration by segment fare versus proration by segment fare.

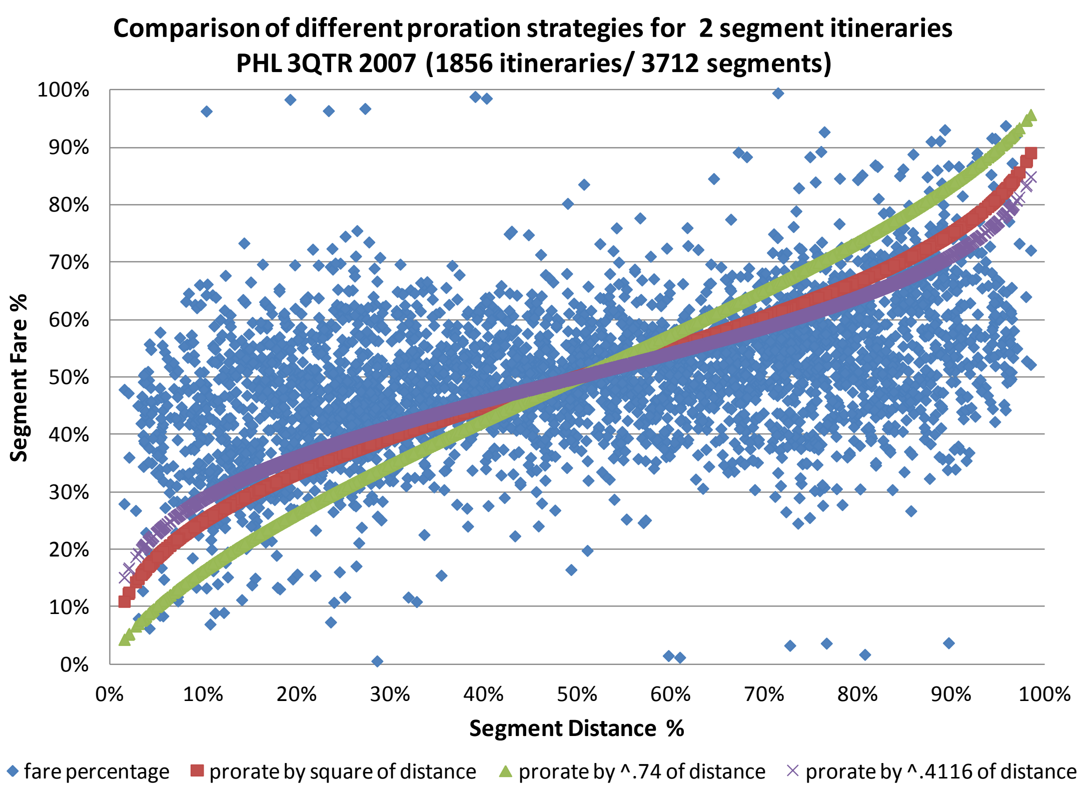



**Figure 13 Comparison of different proration approximation techniques for 2 segment itineraries**

Figure 13 shows an analysis of 1856 Itineraries for PHL airport third quarter 2007. Each of these itineraries had two flight segments which could individually be analyzed in the BTS DB1B database for average fares. Therefore, with this data a comparative analysis is shown between the different approximating techniques to proration by segment fare versus proration by segment fare.

Clearly in these examples none of the approximation techniques are great fits to the proration by segment fares technique. However it is clear that the curve at the higher end, 70% to 90%, clearly dips and the square and .4116 techniques reflect this dip. Also, segment fares are not available for all itinerary segments and the approximation techniques eliminate variances between these segment fare percentages. Therefore, in order to avoid adding another source of variance in the source data for the ASOM, proration based on the square root of the segment distance is used in this study.

### 3.2.2. Airline profit model

Further investigation of the BTS DB1B "Market" database reveals that some of the revenue collected from airfares actually does not contribute towards airline profits. The airlines add taxes and fees to the cost of the airline ticket when purchased and therefore these taxes and fees must be removed from the airfare for accurate airline revenue versus cost analysis. Additionally, revenue from cargo flown on passenger flights and revenue from airline bag, cancelation, change, pets, and frequent flyer charges are not included in the DB1B airfare and must be included. The resulting adjusted airfare provides an improved representation of airline revenue per itinerary.

The domestic taxes and fees not included in the DB1B consist of passenger ticket taxes, flight segment taxes, and passenger facility charges. The amount a passenger pays in taxes and fees on a ticket varies according to his itinerary, including the number of times he or she boards a new flight and at what airports. (De Neufville et al. 2003) The passenger ticket taxes were found to represent 7.5% of the ticket airfare and the domestic flight segment tax was set at $3.60 as of Jan 2009. (ATA 2011) The Federal Aviation Administration (FAA) reports the Passenger Facility Charges (PFC) for major airports. (FAA 2011) The FAA allows for the collection of PFC fees up to $4.50 for every enplaned passenger at commercial airports controlled by public agencies. The FAA then provides these funds to airports to fund FAA-approved projects that enhance safety, security, or capacity, reduce noise, or increase air carrier competition. The average PFCs for the airports examined in this study were $3.63.

The airlines also include a "September 11" security fee in the airfare reported in the DB1B. This fee is imposed on passengers of domestic and foreign air carriers for air transportation that originates at airports in the United States. The fee, which is collected at the time the ticket is bought, is $2.50 per enplanement and is imposed on not more than two enplanements per one-way trip. The fees are collected by the direct air carriers, who must remit the fees to the Transportation Security Administration on a monthly basis. (ATA 2011)

One must therefore take the ticket price and subtract out the taxes and fees collected to obtain the revenue that the airline keeps. There are also other revenues besides the airline ticket revenue that the airline obtains from each passenger flight. We discuss these next.

Examination of airline revenue reports reported in the Aviation Daily, showed substantial revenue gained by the airlines from cargo flown on passenger flights, airline baggage fees, cancelation fees, change fees, transportation of pets, and frequent flyer charges. The revenue realized by airlines from freight and mail on passenger flights was found to be 2.4% of airfare, from Aviation Daily Airline Revenue reports. By aggregating the revenue from fees and dividing by passenger enplanements, this revenue was found to be $10.17 per passenger enplanement (see Table 11).

**Table 11 Airline revenue from Aviation Daily airline revenue reports**

| | | 2008** | 2009 |
|---|---|---|---|
| Ancillary Fees* | | $ 7.50 | $ 10.17 |
| | Bags | $ 2.09 | $ 3.54 |
| | Cancel | $ 2.20 | $ 3.08 |
| * Bags, Cancel/Change, Pets, Freq Flyer | | | |
| ** Based on 3rd & 4th Quarter | | | |

Thus to adjust the DB1B airfares to reflect true revenue from passengers, the airfare must be reduced by 5.1% (7.5% (passenger ticket taxes) - 2.4% (freight/ mail revenue)) and increased by $0.44 ($10.17 (extra fees) - $3.60 (flight segment tax) - $3.63 (PFCs) - $2.50 (September 11 fee)). For the purposes of ASOM analysis all of the segment airfares have been adjusted accordingly.

### 3.2.3. Passenger Demand versus Airfare

Next the individual market passenger demands versus airfare curves were analyzed by aggregating the individual passenger itineraries from the DB1B data. This data transformation to average fare versus cumulative passenger demand was necessary to reflect how passenger demand would vary in response to changes in prices. For example, if there are 2 passengers who bought $500 segment airfares, 19 passengers who bought $300 segment airfares, 29 passengers who bought $200 segment airfares, and 50 passengers who bought $150 segment airfares, then there are 100 passengers who bought segment airfares at an average fare of $200. But, not all passengers bought tickets at $200. Thus, one must consider the curve to determine the loss/gain in passenger demand as prices are increased/ decreased. The above simple example suggests that if the airlines were to increase the average airfares for this segment to $250, then the demand would be reduced to 50 passengers as shown in Table 12, i.e. the cumulative demand of all passengers willing to pay an average of $250 is 50 passengers.

**Table 12 Transformation of DB1B data to passenger demand behavior data**

| DB1B Data | | | | Passenger Behavior Data | |
|---|---|---|---|---|---|
| Segment Airfare | # of Pax | Segment Revenue | Cumulative Revenue | Average Airfare | Cumulative Pax |
| $ 500 | 2 | $ 1,000 | $ 1,000 | $ 500 | 2 |
| $ 300 | 19 | $ 5,700 | $ 6,700 | $ 319 | 21 |
| $ 200 | 29 | $ 5,800 | $ 12,500 | $ 250 | 50 |
| $ 150 | 50 | $ 7,500 | $ 20,000 | $ 200 | 100 |

Since the DB1B data provides individual itinerary quarterly (90 days) data, it is not possible to analyze differences across the days of the week, the times of the day, and various holidays. Additionally, the DB1B database reveals no information about the type of ticket purchased (e.g. refundable, coach, frequent flyer upgrade, weekend stay) or how much in advance these tickets were purchased (e.g. six weeks or 3 weeks ahead or day of purchase). Therefore, all of these average behaviors are assumed to be homogeneous in the data.

### 3.2.4. Fitting the model to the data

In order to analyze economic impacts on passenger demand versus airfare curves the DB1B data must first be fit into market demand versus airfare models. This can still be done using the gravity or exponential model, so the following section discusses a comparison of these techniques to find the best individual market model for the ASOM.

This study examines 600 markets from 10 airports (EWR, JFK, LGA, SFO, DFW, BOS, PHL, BWI, IAD, and DCA) with at least 8 different airfares recorded each quarter from 1st quarter 2005 to 3rd quarter 2010, to determine whether a gravity or exponential model provides the best fit to describe passenger demand versus airfare behavior. Since the DB1B data contains zero fares for frequent flyers and large questionable outlying airfares, different trimming strategies were evaluated. Trimming the left or low airfares was examined for 0%, 5%, 10% and 20% trims. These were combined with right trimming of large airfares at 0%, 10%, 20%, 30%, 40% and 50%. The results of this analysis are shown in Figure 14 and Figure 15. In Figure 14 and Figure 15 the average coefficients of determination are summed across the 10 airports for the different trimming strategies, so a score of 10 is the best possible fit.

For the BTS DB1B market data, the exponential model fits much better that the gravity or power model. For the purposes of using the exponential model in the ASOM model trimming the low (left) airfares by 5% is the best strategy, since trimming the low airfares by more than 10% would remove too much of the data. And trimming the high (right) airfares by 10% to 20% is the best, since trimming the high airfares by more than 20% would also remove distinctions among alternative markets (i.e. markets with more business travelers willing to pay higher airfares).

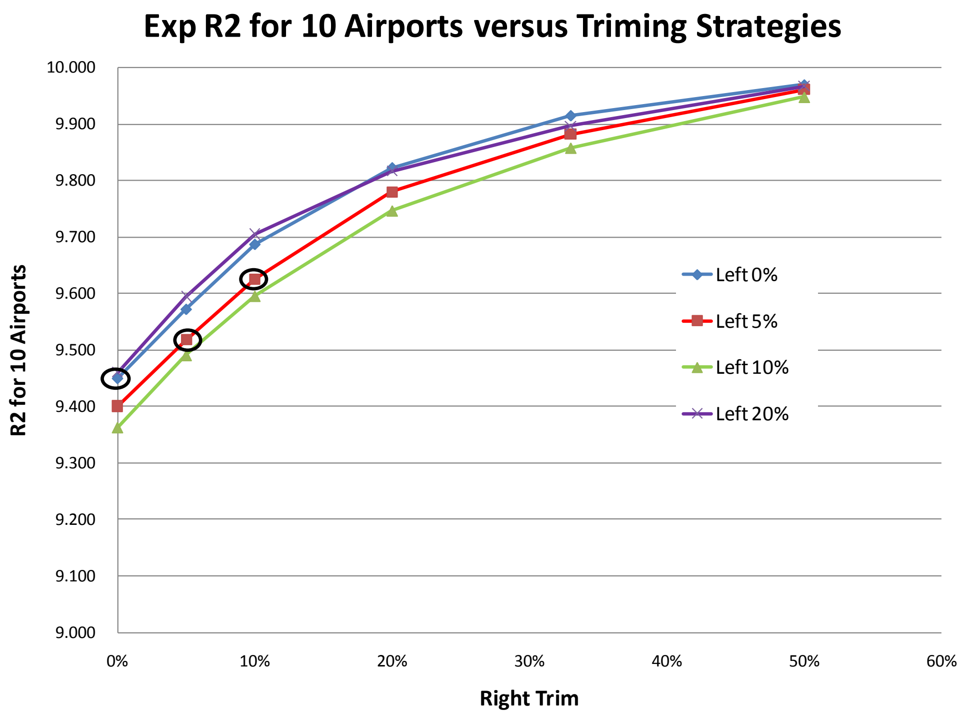



**Figure 14 Coefficients of determination (R2) for the exponential demand model for 3rd quarter 2007**

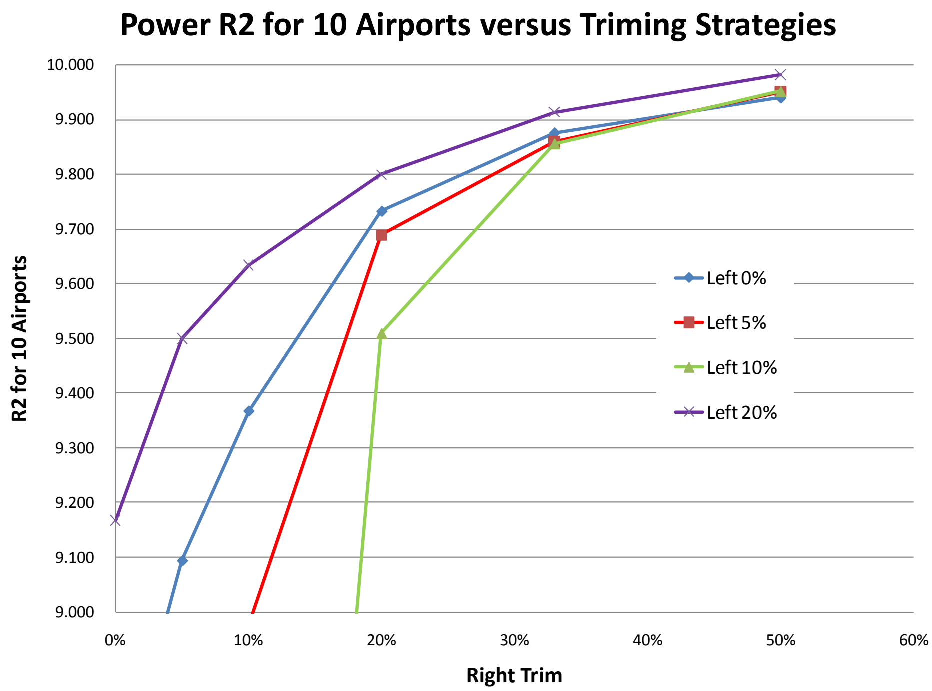



**Figure 15 Coefficients of determination (R2) for the gravity demand model for 3rd quarter 2007**

Table 13 shows the results of these fits for each of the 10 airports examined. Consistently for both models the more the higher airfares are trimmed, the better the fit. Both models converge on each other when higher airfares are trimmed at 30% or more. The table displays a example of trimming 5% left and 10% right by the notation "L05 R10".

## Table 13 Coefficients of determination (R2) for the exponential and gravity demand models for 3rd quarter 2007

**Left or Low airfares trimmed by 0%**

| 3QTR07 | BASE | | R05 | | R10 | | R20 | | R33 | | R50 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| airport | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power |
| BOS | 0.946 | 0.799 | 0.953 | 0.834 | 0.955 | 0.884 | 0.978 | 0.972 | 0.989 | 0.987 | 0.996 | 0.993 |
| BWI | 0.879 | 0.755 | 0.929 | 0.880 | 0.972 | 0.926 | 0.983 | 0.946 | 0.991 | 0.979 | 0.996 | 0.990 |
| DCA | 0.973 | 0.915 | 0.979 | 0.932 | 0.984 | 0.950 | 0.990 | 0.980 | 0.994 | 0.991 | 0.997 | 0.995 |
| DFW | 0.981 | 0.825 | 0.985 | 0.883 | 0.988 | 0.918 | 0.992 | 0.959 | 0.995 | 0.981 | 0.997 | 0.992 |
| EWR | 0.978 | 0.741 | 0.976 | 0.854 | 0.981 | 0.907 | 0.994 | 0.974 | 0.997 | 0.991 | 0.999 | 0.997 |
| IAD | 0.963 | 0.972 | 0.971 | 0.975 | 0.977 | 0.980 | 0.986 | 0.986 | 0.993 | 0.992 | 0.998 | 0.996 |
| JFK | 0.913 | 0.951 | 0.934 | 0.964 | 0.951 | 0.972 | 0.972 | 0.984 | 0.989 | 0.991 | 0.997 | 0.996 |
| LGA | 0.949 | 0.864 | 0.954 | 0.901 | 0.964 | 0.931 | 0.977 | 0.984 | 0.988 | 0.992 | 0.995 | 0.997 |
| PHL | 0.944 | 0.935 | 0.954 | 0.946 | 0.967 | 0.955 | 0.982 | 0.969 | 0.992 | 0.983 | 0.997 | 0.991 |
| SFO | 0.925 | 0.892 | 0.936 | 0.924 | 0.948 | 0.944 | 0.968 | 0.977 | 0.986 | 0.989 | 0.996 | 0.992 |
| sum | 9.4499 | 8.64991 | 9.5722 | 9.0932 | 9.6872 | 9.36719 | 9.8228 | 9.7327 | 9.915 | 9.8762 | 9.9695 | 9.94 |

**Left or Low airfares trimmed by 5%**

| 3QTR07 | L05 | | L05 R05 | | L05 R10 | | L05 R20 | | L05 R33 | | L05 R33 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| airport | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power |
| BOS | 0.941 | 0.697 | 0.948 | 0.716 | 0.951 | 0.828 | 0.973 | 0.963 | 0.986 | 0.985 | 0.996 | 0.994 |
| BWI | 0.881 | 0.720 | 0.928 | 0.845 | 0.962 | 0.920 | 0.985 | 0.946 | 0.992 | 0.983 | 0.998 | 0.994 |
| DCA | 0.973 | 0.895 | 0.976 | 0.920 | 0.980 | 0.941 | 0.988 | 0.977 | 0.993 | 0.990 | 0.997 | 0.996 |
| DFW | 0.977 | 0.707 | 0.981 | 0.794 | 0.983 | 0.899 | 0.988 | 0.950 | 0.993 | 0.978 | 0.996 | 0.994 |
| EWR | 0.974 | 0.622 | 0.974 | 0.772 | 0.978 | 0.823 | 0.992 | 0.966 | 0.996 | 0.987 | 0.998 | 0.997 |
| IAD | 0.959 | 0.961 | 0.966 | 0.967 | 0.974 | 0.976 | 0.983 | 0.985 | 0.992 | 0.992 | 0.998 | 0.997 |
| JFK | 0.898 | 0.942 | 0.924 | 0.957 | 0.943 | 0.967 | 0.967 | 0.982 | 0.982 | 0.991 | 0.995 | 0.997 |
| LGA | 0.942 | 0.695 | 0.946 | 0.773 | 0.955 | 0.819 | 0.969 | 0.979 | 0.983 | 0.990 | 0.993 | 0.996 |
| PHL | 0.940 | 0.834 | 0.950 | 0.849 | 0.961 | 0.871 | 0.977 | 0.960 | 0.990 | 0.975 | 0.996 | 0.991 |
| SFO | 0.916 | 0.872 | 0.924 | 0.910 | 0.939 | 0.935 | 0.957 | 0.978 | 0.977 | 0.988 | 0.995 | 0.995 |
| sum | 9.4007 | 7.94692 | 9.5178 | 8.5016 | 9.6254 | 8.97815 | 9.7798 | 9.689 | 9.882 | 9.8595 | 9.9612 | 9.9512 |

**Left or Low airfares trimmed by 10%**

| 3QTR07 | L10 | | L10 R05 | | L10 R10 | | L10 R20 | | L10 R33 | | L10 R50 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| airport | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power |
| BOS | 0.946 | 0.626 | 0.950 | 0.758 | 0.952 | 0.609 | 0.966 | 0.920 | 0.981 | 0.984 | 0.995 | 0.993 |
| BWI | 0.840 | 0.576 | 0.920 | 0.714 | 0.959 | 0.845 | 0.985 | 0.935 | 0.991 | 0.977 | 0.998 | 0.995 |
| DCA | 0.976 | 0.573 | 0.978 | 0.909 | 0.983 | 0.947 | 0.986 | 0.979 | 0.991 | 0.990 | 0.995 | 0.997 |
| DFW | 0.972 | 0.127 | 0.975 | 0.705 | 0.979 | 0.850 | 0.986 | 0.917 | 0.989 | 0.976 | 0.994 | 0.993 |
| EWR | 0.976 | 0.230 | 0.974 | 0.702 | 0.977 | 0.766 | 0.989 | 0.946 | 0.995 | 0.988 | 0.997 | 0.997 |
| IAD | 0.958 | 0.961 | 0.965 | 0.973 | 0.971 | 0.976 | 0.981 | 0.984 | 0.990 | 0.992 | 0.998 | 0.997 |
| JFK | 0.908 | 0.911 | 0.925 | 0.949 | 0.945 | 0.939 | 0.966 | 0.980 | 0.982 | 0.990 | 0.994 | 0.997 |
| LGA | 0.933 | (1.793) | 0.935 | 0.688 | 0.940 | (1.042) | 0.967 | 0.924 | 0.980 | 0.989 | 0.991 | 0.997 |
| PHL | 0.939 | 0.911 | 0.950 | 0.914 | 0.960 | 0.932 | 0.974 | 0.953 | 0.988 | 0.983 | 0.996 | 0.992 |
| SFO | 0.914 | 0.779 | 0.919 | 0.891 | 0.930 | 0.920 | 0.947 | 0.971 | 0.972 | 0.989 | 0.990 | 0.995 |
| sum | 9.3634 | 3.90078 | 9.491 | 8.2039 | 9.5959 | 6.74241 | 9.7469 | 9.5093 | 9.858 | 9.8565 | 9.948 | 9.9521 |

**Left or Low airfares trimmed by 20%**

| 3QTR07 | L20 | | L20 R05 | | L20 R10 | | L20 R20 | | L20 R33 | | L20 R50 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| airport | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power | Exp | Power |
| BOS | 0.962 | 0.959 | 0.969 | 0.961 | 0.971 | 0.959 | 0.981 | 0.976 | 0.988 | 0.989 | 0.995 | 0.998 |
| BWI | 0.814 | 0.621 | 0.882 | 0.855 | 0.954 | 0.938 | 0.989 | 0.969 | 0.990 | 0.975 | 0.998 | 0.997 |
| DCA | 0.989 | 0.978 | 0.990 | 0.977 | 0.991 | 0.973 | 0.994 | 0.986 | 0.996 | 0.997 | 0.998 | 0.999 |
| DFW | 0.987 | 0.911 | 0.989 | 0.935 | 0.991 | 0.958 | 0.994 | 0.976 | 0.997 | 0.989 | 0.998 | 0.998 |
| EWR | 0.987 | 0.910 | 0.986 | 0.936 | 0.981 | 0.943 | 0.989 | 0.977 | 0.995 | 0.993 | 0.998 | 0.998 |
| IAD | 0.972 | 0.992 | 0.975 | 0.993 | 0.981 | 0.993 | 0.987 | 0.994 | 0.991 | 0.997 | 0.998 | 0.999 |
| JFK | 0.914 | 0.956 | 0.938 | 0.965 | 0.952 | 0.972 | 0.973 | 0.985 | 0.987 | 0.993 | 0.997 | 0.998 |
| LGA | 0.969 | 0.917 | 0.968 | 0.941 | 0.971 | 0.950 | 0.974 | 0.965 | 0.987 | 0.992 | 0.995 | 0.998 |
| PHL | 0.933 | 0.985 | 0.962 | 0.989 | 0.967 | 0.990 | 0.978 | 0.993 | 0.990 | 0.996 | 0.996 | 0.999 |
| SFO | 0.933 | 0.937 | 0.936 | 0.946 | 0.946 | 0.957 | 0.959 | 0.977 | 0.977 | 0.994 | 0.992 | 0.998 |
| sum | 9.4605 | 9.16739 | 9.5948 | 9.4992 | 9.7051 | 9.63396 | 9.8168 | 9.7997 | 9.8966 | 9.9134 | 9.967 | 9.982 |

This analysis shows independent of the trimming strategy the exponential model is the best fit for individual market demand versus airfare curves.

## 3.3. Capturing economic fluctuations in airline macroeconomic models

When analyzing the impacts of economic conditions on airline and passenger behavior, macroeconomic models must reflect these impacts for airline costs and revenues as well as passenger price elasticity. While the method for capturing fuel price changes in airline costs is straight forward and intuitive, the methods for capturing economic impacts for airline revenue and price elasticity are more complex.

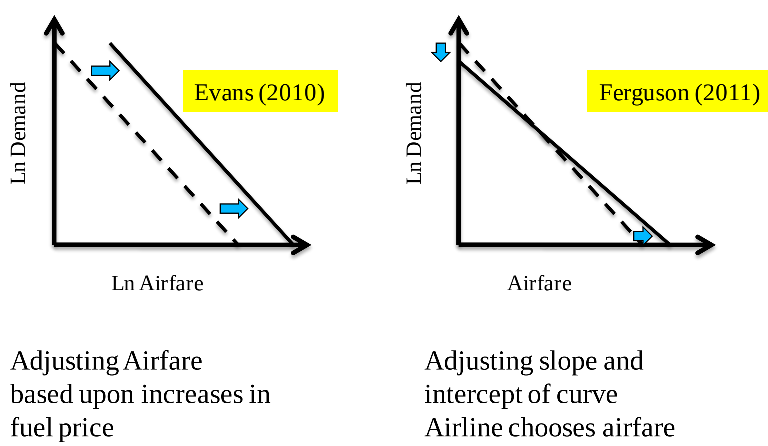



**Figure 16 Different strategies for adjusting revenue to reflect economic changes**

Figure 16 compares Evans technique, discussed in chapter 2, for adjusting the price elasticity curve for increases in fuel prices versus the technique used in this dissertation. Clearly, just shifting the curve to represent increased airfares from fuel price increases falsely inflates the intercept of the curve (demand coefficient) and does not follow the market's passenger demand versus airfare pattern. The technique applied in this study examines how passenger price versus demand curves adjust, both in slope and intercept, as economic factors change. The Airport Schedule Optimization Model used in this study then chooses the optimum airfares to maximize airline profits for the schedule and follow individual market demand versus airfare curves.

## 3.4. Analysis of fluctuations in fuel prices and national unemployment rates effects on Passenger behavior

In order to develop a model to reflect changes in airline and passenger behavior in response to economic conditions the following analysis was conducted.

### 3.4.1. Scope of Analysis

This analysis examines 600 markets with at least 8 different price points, for 23 quarters (1 quarter 2005 to 3rd quarter 2010) and from 10 airports (EWR, JFK, LGA, SFO, DFW, BOS, PHL, BWI, IAD, DCA) as shown in Table 14. In Table 14 a large market represents more than two percent of the passenger demand for the airport. This analysis examines the effects from fluctuations in fuel prices and national unemployment rates effects on passenger behavior (slope and intercept of demand versus airfare curves).

**Table 14 Number of markets examined for effects from economic fluctuations by size and airport**

| Airport | small market | large market | Total Markets |
|---|---|---|---|
| **BOS** | 33 | 19 | 52 |
| **BWI** | 27 | 21 | 48 |
| **DCA** | 39 | 14 | 53 |
| **DFW** | 90 | 12 | 102 |
| **EWR** | 42 | 19 | 61 |
| **IAD** | 50 | 13 | 63 |
| **JFK** | 28 | 18 | 46 |
| **LGA** | 37 | 16 | 53 |
| **PHL** | 58 | 19 | 77 |
| **SFO** | 26 | 19 | 45 |
| **Grand Total** | **430** | **170** | **600** |

Departures from the airports examined in this analysis represented 17.26% of the US domestic departures in 2007, see Table 15.

**Table 15 Percentage of 2007 US domestic flights from airports in this analysis**

| | Airport Name | # of flights |
|---|---|---|
| **PHL** | **Philadelphia International** | 2.10% |
| **LGA** | **LaGuardia** | 1.84% |
| **EWR** | **Newark Liberty International** | 1.70% |
| **JFK** | **Kennedy International** | 1.47% |
| **SFO** | **San Francisco International** | 1.40% |
| **BOS** | **Logan International** | 1.72% |
| **IAD** | **Dulles International** | 1.38% |
| **DCA** | **Ronald Reagan Washington National** | 1.33% |
| **BWI** | **Baltimore/Washington International** | 1.27% |
| **DFW** | **Dallas/Ft Worth International** | 3.06% |
| **Total Percentage of US Domestic Flights** | | 17.26% |

The two favorable trimming strategies identified in the previous section for the best fit of cumulative demand versus average price, a 5% Left trim with a 10% Right trim and a 5% Left trim with a 20% Right trim, are both examined to determine sensitivity to economic fluctuations.

### 3.4.2. Analytical Method

This analysis is done using a tiered regression approach; first 27,600 regressions are performed in Matlab to identify the exponential demand and price coefficients that represent the average price versus cumulative demand curves for the 600 markets for 23 quarters and for two different fitting strategies (600 x23x2=27,600). The market average prices versus cumulative demand curves are fit to the equation below to identify the demand and price coefficients.

$$Passenger\ Demand = Market\ Demand * exp^{-price\ coeff*avg\ airfare}$$

Next a longitudinal multiple-regression is performed in Mini-tab to determine the functional contribution to the variance between these coefficients from changes in fuel prices and national unemployment. Additionally, factors that change over time and between markets are used to develop a better model for exponential coefficients over time and between markets. Specifically this analysis attempt to identify the following functional relationships:

$$Ln\ (Exponential\ Market\ Demand\ Coefficient)$$
$$= intercept + a * fuel\ price + b * unemployment\ rate + c * effective\ number\ of\ airlines + d * daily\ frequency\ of\ flights + e * market\ distance + large\ market\ difference\ from\ small\ markets + airport\ difference\ from\ Boston\ airport$$

$$Exponential\ Price\ Coefficient$$
$$= intercept + a * fuel\ price + b * unemployment\ rate + c * effective\ number\ of\ airlines + d * daily\ frequency\ of\ flights + e * market\ distance + large\ market\ difference\ from\ small\ markets + airport\ difference\ from\ Boston\ airport$$

The following factors are also included in the analysis to capture variances between coefficients for different markets over the 23 quarters of examination. The inverse of the Herfindahl-hirschman index (Hirschman 1964) or effective number of airlines for each market is included in the model to capture differences in the coefficients that can be explained by competition differences. The average daily frequency of flights to the market is included in the model to capture differences in the coefficients that can be explained by frequency of service. The market distance is included in the model to capture differences in the coefficients that can be explained by this factor. The correlation analyses of these factors are shown in Table 16.

**Table 16 Correlation analysis of market factors**

| | | Market Distance | Effective # of Airlines |
|---|---|---|---|
| Effective # of Airlines | pearson correlation coeff | -0.026 | |
| | P-value | 0.002 | |
| | | | |
| Daily Frequency of Service | pearson correlation coeff | -0.054 | 0.004 |
| | P-value | 0 | 0.632 |

Dummy variables (0 or 1) are included in the regression to capture differences in seasonality, market size and differences between airports. Dummy variables for 1st, 2nd and 4th quarter capture the differences in the coefficients from these quarters compared to 3rd quarter. A dummy variables for larger markets captures the differences in the coefficients from large markets compared to small markets. Dummy variables for EWR, JFK, LGA, SFO, DFW, PHL, BWI, IAD, and DCA capture the differences in the coefficients from these airports compared to BOS.

Lastly a longitudinal regression is performed in Mini-tab to determine the functional contribution to the variance between these coefficients from changes in fuel prices and national unemployment. These coefficients of change for the market demand and price coefficients are then regressed against market distance to determine the impact market distance has on the impact of fuel prices and national unemployment on the exponential demand function.

### 3.4.3. Results of analysis

Two trimming strategies were evaluated for 12 different models to capture the effects of changes in economic conditions on the individual market demand and price coefficients. A model for all 600 markets and all airports, a model for the 170 major market (markets that represent 2% or more of airport demand) as shown in Table 14, and 10 individual airport models for all markets serving the respective airport were evaluated. These models were developed for two trimming strategies, the first trimming strategy (L05R20) removed 5% of the smallest or discount fares and removed 20% of the highest fares. Since this model was fitted for average price versus cumulative demand these higher fares were still represented in the average fares for all airfares remaining. The second trimming strategy (L05R10) removed 5% of the smallest or discount fares and removed 10% of the highest fares.

The results of these 48 longitudinal multiple-regressions (2 coefficients x 12 models x 2 trimming strategies) are shown in Table 17. The analysis shows how the individual marker cumulative demand versus average airfare curves change in response to fluctuations in economic conditions. The green highlighted cells show positive coefficients for changes in fuel prices or national unemployment rates. The yellow cells highlight coefficients chosen for use in the ASOM to reflect the fluctuations in economic conditions. The empty cells represent cases where no significant statistical relationships were found between demand and price coefficients to changes in fuel prices or national unemployment rates.

**Table 17 Impact of fluctuations in economy on exponential demand and price coefficients**

| | Effect on Exponential Demand Coefficient | | | | Effect on Exponential Price Coefficient | | | |
|---|---|---|---|---|---|---|---|---|
| | 1$ increase in Fuel Price | | 1% increase in Unemployment | | 1$ increase in Fuel Price | | 1% increase in Unemployment | |
| **markets** | **L05R10** | **L05R20** | **L05R10** | **L05R20** | **L05R10** | **L05R20** | **L05R10** | **L05R20** |
| **all** | -0.84% | -0.52% | -0.49% | -0.33% | -14.85% | -12.59% | -2.62% | -1.80% |
| **major** | -0.99% | -0.67% | -0.58% | -0.43% | -20.02% | -15.34% | -4.43% | -3.16% |
| **DFW** | | | -0.24% | | -14.62% | -13.52% | -2.04% | -1.29% |
| **BOS** | | | | | -7.61% | -6.81% | 1.43% | 1.56% |
| **LGA** | -1.04% | | | | -5.99% | -4.00% | 0.83% | 1.57% |
| **JFK** | 1.60% | 1.80% | | | -10.38% | -9.49% | -1.38% | -1.17% |
| **EWR** | -3.69% | -3.50% | -1.05% | -0.97% | -7.29% | -5.91% | -3.73% | -3.20% |
| **SFO** | -1.38% | -1.35% | -1.06% | -0.85% | -20.23% | -18.86% | -3.78% | -3.10% |
| **PHL** | | 0.76% | -0.18% | | -4.58% | | | |
| **BWI** | | | -0.61% | | -20.70% | -10.47% | -5.54% | -3.33% |
| **IAD** | -1.94% | -2.19% | -0.93% | -0.86% | -25.62% | -25.50% | -5.47% | -5.09% |
| **DCA** | -0.94% | -0.88% | -0.52% | -0.39% | -22.54% | -21.27% | -4.27% | -3.47% |

The trimming strategy of a left trim of 5% and right trim of 20% seems to be less sensitive to fluctuations in economic factors. Therefore this strategy will be used for fitting exponential passenger demand versus average airfare curves in for the ASOM analysis shown in chapter 5. Additionally, large market exponential passenger demands versus average airfare curves were found to be more sensitive to fluctuations in economic factors than small markets. So the percentage change factor for all markets will be used for ASOM analysis to conservatively represent the impacts of fluctuations in the economy, these factors are highlighted in yellow in Table 17.

The analysis of individual airports showed that for several airports the demand coefficient was not sensitive to changes in the economy. On the other hand JFK and PHL showed positive increases in demand due to economic conditions. We presume that these anomalies reflect increased demand due to airport business expansion and since this information is not reflected in any data provided, it is incorrectly reporting the source of demand increases to the economic changes.

The analysis showed that only PHL's price coefficient was insensitive to changes in the economy. And in most cases other than BOS and LGA, when the economy worsened either through increased fuel prices or increased unemployment rates passengers became less price sensitive. In other words, as the economy worsened, although total demand decreased, passenger who did fly were less sensitive to price changes.

Further Longitudinal analysis of the sensitivity of the demand and price coefficients to market distance did not reveal any statistically significant results.

**Table 18 Effects on exponential demand and price coefficients from economic or market changes**

| Effects from: | Left 5% and Right 20% Trimming | |
|---|---|---|
| | % change in Demand Coefficient | % change in Price Coefficient |
| $1 increase in Fuel Price | -0.52% | -12.59% |
| 1% increase in Unemployment | -0.33% | -1.80% |
| Added airline at airport | | -2.71% |
| Additional Daily flight for market | 0.94% | -1.27% |
| Additional 100 miles of Market Distance | 0.57% | -4.59% |
| Model $R^2$ | 54% | 37% |

Table 18 shows the final results from this analysis of economic fluctuations on exponential fits of passenger versus average airfare curves. As previously discussed an increase in fuel prices will reduce passenger demand by 0.52% and reduce passenger price sensitivity by 12.59%. Similarly a 1% increase in the unemployment rate will reduce passenger demand by 0.33% and reduce passenger price sensitivity by 1.80%. The analysis also showed that when an additional airline leaves? a market, passenger price sensitivity is reduced 2.71% and passenger demand is reduced 0.94%. Similarly adding additional flights per day for a market reduces the price sensitivity of the passenger by 1.27%.

### 3.4.4. Further examination of alternative Models

Table 18 shows that the model selected to represent the impact of economic fluctuations on passenger demand versus airfare market curves only explains 37% of the variability for the price coefficient and 54% of the variability for the demand coefficient. Therefore, an additional 6 models are examined to determine if there are better model fits within the subsets of the data as shown in Table 19. A model for markets with individual exponential fits of 95% $R^2$ or better for all 23 quarters and a similar model for the major markets that fit the same criteria are examined. A model for markets 125 to 1125 miles apart and a similar model for the major markets that fit the same criteria are examined. A model for markets with 2-3 airlines in competition and a similar model for the major markets that fit the same criteria are examined.

**Table 19 Best fit comparison of different models Coefficients of Determination ($R^2$) for demand and price coefficients**

| Models: | % data | Coefficient of determination | | % change from $1 increase in Fuel Price | | % change from 1% increase in Unemployment | |
|---|---|---|---|---|---|---|---|
| | | demand coefficient | price coefficient | demand coefficient | price coefficient | demand coefficient | price coefficient |
| all | 100% | 54% | 37% | -0.52% | -12.59% | -0.33% | -1.80% |
| 2-3 airlines per market | 86% | 54% | 36% | -0.49% | -11.93% | -0.28% | -1.70% |
| Markets b/w 125-1125 miles | 75% | 59% | 35% | -0.67% | -13.39% | -0.24% | -1.72% |
| 95% fit for all markets | 55% | 59% | 37% | -0.80% | -12.95% | -0.30% | -1.75% |
| all Major markets | 28% | 33% | 54% | -0.67% | -15.34% | -0.43% | -3.16% |
| Major markets w/ 2-3 airlines | 24% | 32% | 54% | -0.61% | -14.11% | -0.41% | -3.17% |
| Major markets b/w 125-1125 miles | 18% | 39% | 51% | -0.87% | -15.97% | -0.30% | -3.01% |
| Major markets w/ 95% fit | 6% | 69% | 78% | | -15.63% | -0.64% | -5.62% |
| DFW | 17% | 61% | 62% | | -13.52% | -0.64% | -1.29% |
| PHL | 13% | 65% | 20% | **0.76%** | | | |
| EWR | 10% | 69% | 27% | -3.50% | -5.91% | -0.97% | -3.20% |
| IAD | 10% | 59% | 33% | -2.19% | -25.50% | -0.86% | -5.09% |
| BOS | 9% | 47% | 24% | | -6.81% | | **1.56%** |
| LGA | 9% | 58% | 30% | | -4.00% | | **1.57%** |
| DCA | 9% | 71% | 17% | -0.88% | -21.27% | -0.39% | -3.47% |
| JFK | 8% | 37% | 28% | **1.80%** | -9.49% | | -1.17% |
| BWI | 8% | 29% | 30% | | -10.47% | | -3.33% |
| SFO | 7% | 58% | 49% | -1.35% | -18.86% | -0.85% | -3.10% |

### 3.4.5. Conclusions and Observations

These results quantify the impact of fluctuations in fuel prices and national unemployment rates on domestic passenger demand behavior. This passenger demand versus airfare behavior must be understood since passengers are a key component of the national commercial air transportation system.

This analysis shows a new metric, from these coefficients of change shown in Table 17 that can be used to understand how resilient passenger demand and price sensitivity are at specific airports to economic fluctuations. This analysis also shows a new metric might be available to measure how a market's passenger demand and price sensitivity change as a function of airline competition. In particular, these 10 airports resiliency to fuel price changes fell into three groups based upon the % change in their demand versus airfare price coefficients in response to a $1 increase in aviation fuel prices (~-5%, ~-10%, and ~-20%). BOS, LGA, and EWR price coefficients changed around -5% for a $1 increase in aviation fuel prices. PHL and JFK price coefficients changed around -10% for a $1 increase in aviation fuel prices. DFW, SFO, BWI, IAD, and DCA price coefficients changed around -20% for a $1 increase in aviation fuel prices. Thus BOS, LGA, and EWR markets are more resilient to increases in fuel prices.

The results of this analysis are shown in Table 19. The results show that depending on the airport or subset of markets chosen for a model a $1 increase in fuel prices would change the demand coefficient between -3.5% to 1.8% and would change the price coefficient between -25.5% to -4.0%. This analysis also shows that depending on the airport or subset of markets chosen for a model a 1% increase in national unemployment rate would change the demand coefficient between -0.97% to -0.24%

and would change the price coefficient between -5.62% to 1.57%. And while a few models represented a small subset of the markets well, that these models would not represent all markets well. On the other hand, most of the subset models did not represent changes in demand and price coefficients do to economic fluctuations as well as the general model selected earlier for use in the ASOM. While the general model may not appear to be the best model, it produces results consistent with what we would expect from the ASOM. Specifically, the ASOM reduces passenger demand, increases airfares, and marginal changes airline profits in response to increased fuel prices.

We will use the results of this analysis within the ASOM model and thereby be able to model events for which there is no historical data that reflects the exact characteristics of a given scenario. That is, we can infer what might happen when fuel prices are increasing during good economic times and recessions as well as model the impact of an airline leaving/arriving at a given airport. We begin with the general demand curves but include shifts in the slope or the intercept to reflect the requisite changes in passenger sensitivity.

# CHAPTER 4 – MODELING DOMESTIC AIRLINE SCHEDULING OF NON-STOP DIRECT MARKETS WITH THE AIRPORT SCHEDULE OPTIMIZATION MODEL

The Airport Schedule Optimization Model (ASOM) is a multi-commodity flow model that optimizes the domestic schedule of an airport while satisfying market demand. It serves as an aggregate planning model for the airline industry at a given airport determining the schedule of all domestic flights. It selects the timing of all flights, the airfares to charge (based on the demand elasticity curves) and the size of the aircraft. One can therefore use the ASOM model to examine the effects of fuel price changes, changes airline operational costs and/or adjustments to airport capacity on likely airport schedules. This is a unique capability only found in one other airport schedule optimization model, the original ASOM model before changes were made for this dissertation. (L. T. Le 2006) Major changes were made to that model to allow it to be used for any US airport and include allowing hub airports where maintenance and significant overnighting takes place, airports that have significant international markets and ones that have significantly different capacity conditions. In addition, the model formulation was changed to allow more efficient branching by requiring that at most one arrival and one departure would be allowed between any two airports in any 15 minute period. This is a reasonable assumption based on the fact that the ASOM model does not model inter-airline competition and if there were enough demand on a single leg during a given period, the model would choose an aircraft size that would accommodate this traffic. Historic analysis of domestic flight schedules show that less than 5% of the time that more than one arrival or departure be scheduled for the same market in the same 15 minute period.

The ASOM model aggregates individual airline behavior to maximize profits for domestic non-stop markets at an airport for a fixed capacity level, while maintaining service to international and non-commercial markets. The ASOM generates a daily flight schedule to service passenger demand for passengers flying on domestic direct non-stop itineraries as well as passengers connecting on additional flights to another domestic market. An example of a few non-stop markets served by John F. Kennedy International Airport is shown in Figure 17.

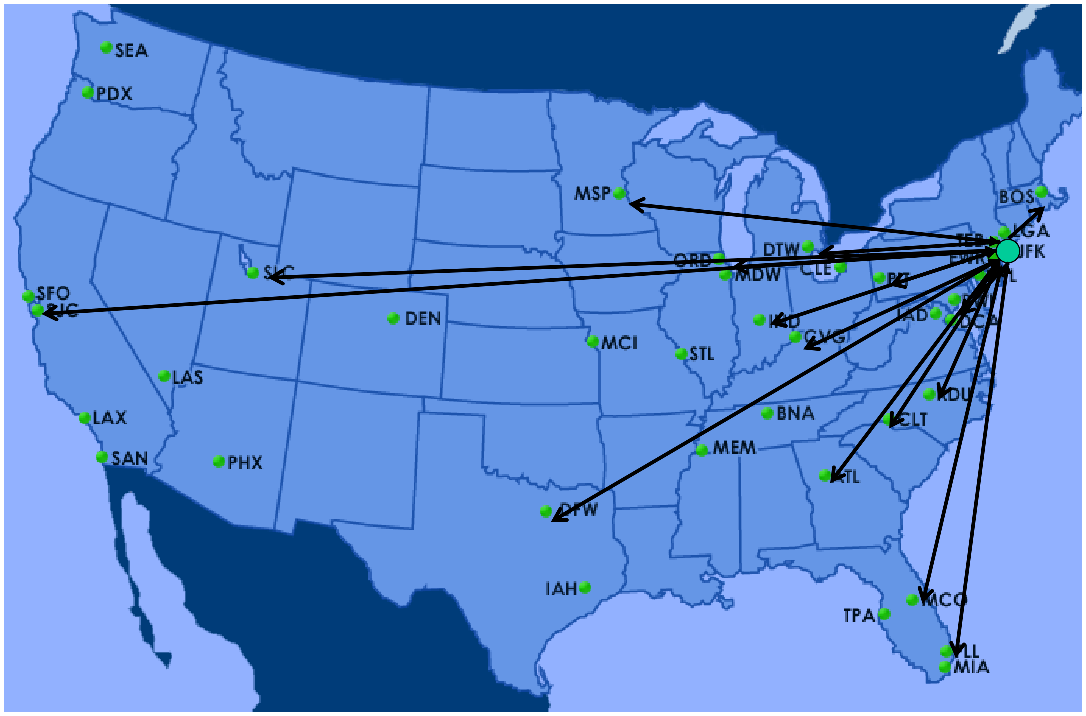



**Figure 17 Example of network of non-stop direct domestic markets for New York Metroplex**

## 4.1. Airport Schedule Optimization Model (ASOM) Overview

The ASOM model is summarized in Figure 18. The model uses as its base line the summer 2007 schedule and historical information regarding airport capacity limits, airline fuel prices, operational flight costs by aircraft type for each market, and market demand at given posted prices, i.e. the demand curve based on the 10% ticket sample. The operational flight costs and fuel burn rates for aircraft were averaged from airline reported cost data contained in the BTS P-52 database from third quarter 2002 to fourth quarter 2010.

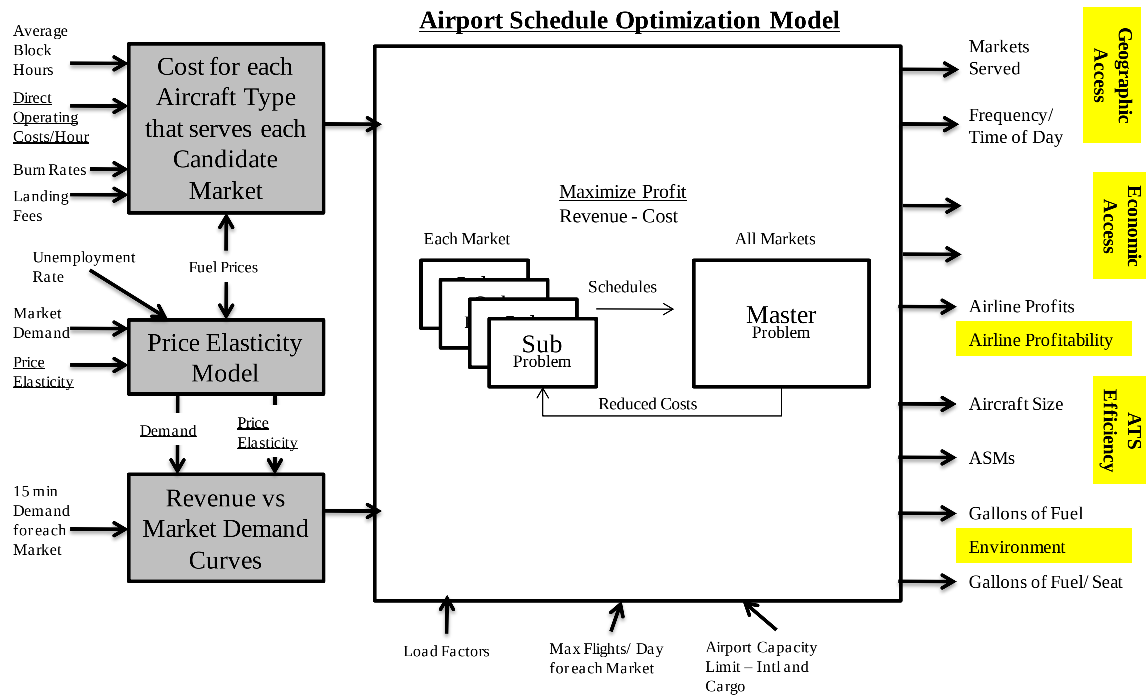



**Figure 18 The Airport Schedule Optimization Model (ASOM)**

Runway capacities were taken from the FAA 2004 airport benchmark report (Barkeley 2004) and verified using the FAA Aviation System Performance Metrics (ASPM) database (FAA 2007). However, these capacities reflect all arrivals and departures into the airport. To obtain commercial domestic runway capacities, we subtract out the average number of scheduled international flights and cargo flights during each 15-minute. Because of treaties and other priority arrangements, the ASOM model assumes that this capacity does not compete with domestic passenger capacity but, rather limits the capacity available.

Historic hedged fuel prices as reported by the airlines were derived using the BTS P52 database. (U.S. DOT/BTS 2010) The baseline price of $2 per gallon price observed in 3QTR 2007 was used as the baseline initial conditions.

Operational flight costs were calculated by aircraft type for each market. These operational costs were derived from airline operational cost data reported in the BTS P52 database (U.S. DOT/BTS 2010) and from average scheduled flight times from the FAA ASPM database (FAA 2007). The ASOM can allow all aircraft to be considered for specific markets, whether it was used historically or not. Thus, since both fuel costs and crew costs vary by aircraft type, we apply these costs directly to the overall costs using a linear operating cost model that includes as components: fuel costs, maintenance costs, crew costs and other operating costs such as baggage, ticketing and handling. For more on how these costs were derived, see Ferguson et al. [2011].

Market demand versus airfare functions are derived using the BTS Airline Origin and Destination Survey database (DB1B), containing a 10% sample of reported airline ticket itineraries. (U.S. DOT/BTS 2010) The ASOM model adjusts these curves to reflect demand and price elasticity changes as fuel prices are changed, in terms of changes in intercept and slope respectively, as was discussed in Chapter 3 of this dissertation. For every $1 increase in hedged aviation fuel prices passenger demand is reduced 0.52% and the price coefficient or passenger sensitivity to airfare changes is reduced 12.59%. The general form of the market demand versus airfare functions is shown in Equation

14. Chapter 3 of this dissertation describes the derivation of the price elasticity model through analysis on demand and price coefficients over time.

$$Demand = (Demand\_Coeff) * e^{price\_coeff*airfare}$$

**Equation 14 Exponential Demand versus Airfare**

These market demand versus airfare functions are used to select optimal airfares for the optimal airport schedule. Thus, the ASOM model serves as an aggregate planning model for the airline industry at a given airport determining the schedule of all domestic flights into that airport, the posted prices and the size of the aircraft serving each flight.

The output of the ASOM is a feasible schedule to each profitable market where a scheduled includes the specification of the aircraft size, the frequency of service and the specific period that each flight is flown (in 15-minute increments). In addition, the model outputs the average price charged and thereby the average revenue per flight as well as the daily profit, fuel used.

This ASOM model outputs will be compared to historical data that was collected during the Summer 2007 period for validation purposed. Descriptions of the analysis of historical data can be found in (Ferguson et al. 2011)(Ferguson et al. 2010)(Ferguson et al. 2009b)(Ferguson, K. Sherry, et al. 2009).

## 4.2. Preprocessing data for the ASOM

Modeling airline scheduling decisions usually require proprietary cost and revenues data along with constraints of airline business models. We use aggregate data across airlines available in public databases. Aggregate data is effective in reducing the inherent noise in any data set, especially for airlines with little public data. Parameter estimation for scheduling models consists of building the timeline networks and calculating revenue functions.

### 4.2.1. Historic service for daily markets

Daily markets are specified as markets with an average of at least one reported commercial domestic flight per day in the FAA's ASPM database. (FAA 2010) These daily frequencies of service are used as input for the ASOM model, to limit ASOM schedules to the demand historically observed for each market. The average daily demand, aircraft size and load factors are calculated for all daily markets using the BTS T100 database. (U.S. DOT/BTS 2010) These factors are used as inputs for the ASOM model and constrain this model of a profit seeking aggregate airline from exceeding historic average daily load factors. The supply of seats arriving and departing for daily markets is calculated from the ASPM database, so the average daily market demand can be allocated to each 15 minute time window. Unlike previous aggregate models discussed in chapter 2, this allocation of demand considers demand by time of day and determines flight schedules (both time of flight and size of aircraft) so as to satisfy the demand at competitive prices.

### 4.2.2. Aircraft seat classes and average market flight costs

Aircraft direct operating costs, flights hours, and gallons of fuel issued for flights operations reported by the airlines for different aircraft types are found in the BTS P52 database. (U.S. DOT/BTS 2010) This data is combined with the average aircraft sizes as reported in the BTS T100 database, to evaluate aircraft costs by seat classes of aircraft as shown in Table 20.

This data is aggregated by seat class as shown in Table 21 to provide aircraft direct operating costs by hour and average fuel burn rates by aircraft class for a current aircraft scenario. Note current reporting aircraft are absent for the 200 and 350 seat classes.

## Table 20 BTS P52 reported costs, flight hours and gallons issued 3QTR 2002 – 4QTR2010

| Aircraft Name | Air Fuel Issued | Total Air Hours | Total Flights $ | Total Fuel $ | Avg Seats |
|---|---|---|---|---|---|
| **⊟25** | **573,289** | **2,772** | **2,658,584** | **947,504** | **31** |
| British Aerospace Jetstream 41 | 33,486 | 185 | 171,115 | 47,609 | 30 |
| Dassault-Breguet Mystere-Falcon | 2,404 | 6 | 14,256 | 9,186 | 15 |
| Dehavilland Dhc8-100 Dash-8 | 45,871 | 224 | 229,236 | 117,181 | 37 |
| Dehavilland Dhc8-200q Dash-8 | 78,240 | 329 | 384,947 | 126,905 | 37 |
| Dornier 328 | 1,957 | 10 | 11,526 | 2,088 | 32 |
| Dornier 328 Jet | 65,247 | 148 | 151,197 | 61,217 | 32 |
| Embraer Emb-120 Brasilia | 176,007 | 1,016 | 930,287 | 359,298 | 30 |
| Saab-Fairchild 340/B | 170,076 | 854 | 766,020 | 224,019 | 34 |
| **⊟50** | **8,589,935** | **19,019** | **26,082,814** | **12,719,710** | **48** |
| Aerospatiale/Aeritalia Atr-42 | 9,136 | 36 | 55,477 | 9,283 | 46 |
| Canadair Rj-100/Rj-100er | 361,640 | 738 | 1,335,160 | 706,772 | 50 |
| Canadair Rj-200er /Rj-440 | 4,060,526 | 9,247 | 14,160,263 | 6,840,976 | 50 |
| Embraer-135 | 477,870 | 958 | 1,240,001 | 718,827 | 38 |
| Embraer-140 | 539,028 | 1,128 | 1,481,180 | 1,072,785 | 44 |
| Embraer-145 | 3,139,725 | 6,909 | 7,807,876 | 3,369,431 | 50 |
| Fokker F28-4000/6000 Fellowship | 2,009 | 2 | 2,857 | 1,636 | 60 |
| **⊟75** | **3,036,901** | **6,623** | **10,125,148** | **5,463,319** | **77** |
| Aerospatiale/Aeritalia Atr-72 | 170,344 | 663 | 1,137,018 | 338,904 | 65 |
| Avroliner Rj85 | 13,783 | 25 | 22,109 | 14 | 87 |
| British Aerospace Bae-146-300 | 78,351 | 92 | 215,788 | 99,378 | 87 |
| Canadair Crj 900 | 597,190 | 1,004 | 1,770,299 | 1,167,686 | 83 |
| Canadair Rj-700 | 1,683,596 | 3,467 | 5,477,380 | 3,163,834 | 68 |
| Dehavilland Dhc8-400 Dash-8 | 200,530 | 524 | 833,386 | 413,604 | 75 |
| Embraer 170 | 228,303 | 732 | 570,970 | 232,515 | 71 |
| Embraer Erj-175 | 64,805 | 117 | 98,198 | 47,384 | 78 |
| **⊟100** | **2,278,738** | **2,402** | **6,629,253** | **3,841,721** | **99** |
| Boeing 727-100 | 89,455 | 74 | 459,196 | 137,200 | 94 |
| Embraer 190 | 439,638 | 606 | 1,601,305 | 971,057 | 100 |
| Fokker 100 | 180,704 | 219 | 416,299 | 151,980 | 100 |
| Mcdonnell Douglas Dc9 Super 87 | 47,186 | 46 | 127,370 | 105,502 | 109 |
| Mcdonnell Douglas Dc-9-10 | 31,215 | 32 | 79,878 | 28,731 | 90 |
| Mcdonnell Douglas Dc-9-15f | 15,112 | 20 | 61,434 | 39,174 | 90 |
| Mcdonnell Douglas Dc-9-30 | 1,231,420 | 1,187 | 3,117,222 | 1,932,425 | 100 |
| Mcdonnell Douglas Dc-9-40 | 244,007 | 219 | 766,548 | 475,652 | 110 |
| **⊟125** | **27,251,996** | **32,338** | **81,309,055** | **47,046,877** | **123** |
| Airbus Industrie A-318 | 172,903 | 196 | 488,438 | 338,213 | 114 |
| Airbus Industrie A319 | 5,965,815 | 7,344 | 19,479,204 | 11,318,197 | 127 |
| Boeing 717-200 | 2,100,535 | 2,517 | 7,367,710 | 3,818,645 | 114 |
| Boeing 737-100/200 | 631,074 | 640 | 1,537,184 | 733,807 | 127 |
| Boeing 737-200c | 125,265 | 117 | 309,217 | 183,635 | 117 |
| Boeing 737-300 | 7,583,485 | 8,762 | 21,227,271 | 11,754,430 | 133 |
| Boeing 737-500 | 2,035,251 | 2,357 | 6,189,121 | 3,441,500 | 115 |
| Boeing 737-700/700lr | 8,033,821 | 9,908 | 23,099,102 | 14,313,398 | 136 |
| Mcdonnell Douglas Dc-8-40 | 3,468 | 2 | 9,673 | 778 | 124 |
| Mcdonnell Douglas Dc-9-50 | 600,379 | 496 | 1,602,135 | 1,144,273 | 125 |
| **⊟150** | **31,099,769** | **31,319** | **94,530,296** | **57,253,928** | **145** |
| Airbus Industrie A320-100/200 | 8,783,805 | 10,032 | 26,972,610 | 16,743,104 | 150 |
| Boeing 727-200/231a | 1,213,988 | 807 | 4,257,409 | 1,897,688 | 141 |
| Boeing 737-400 | 1,703,311 | 1,937 | 5,494,007 | 3,022,761 | 138 |
| Boeing 737-800 | 7,106,670 | 7,700 | 23,304,509 | 13,583,303 | 153 |
| Mcdonnell Douglas Dc9 Super 80/Md8 | 11,978,567 | 10,524 | 33,566,245 | 21,399,313 | 140 |
| Mcdonnell Douglas Md-90 | 313,427 | 319 | 935,517 | 607,758 | 150 |
| **⊟175** | **21,098,940** | **17,559** | **60,980,358** | **38,819,204** | **178** |
| Airbus Industrie A321 | 1,060,516 | 1,073 | 2,842,536 | 1,936,927 | 185 |
| Boeing 737-900 | 811,003 | 849 | 2,352,272 | 1,561,211 | 170 |
| Boeing 757-200 | 16,694,830 | 14,008 | 49,377,616 | 31,022,288 | 183 |
| Boeing 767-200/Er/Em | 2,517,373 | 1,620 | 6,349,241 | 4,260,922 | 171 |
| Mcdonnell Douglas Dc-8-61 | 3,474 | 2 | 14,555 | 7,071 | 180 |
| Mcdonnell Douglas Dc-8-72 | 11,744 | 8 | 44,137 | 30,786 | 180 |
| **⊟225** | **2,828,276** | **1,779** | **9,172,708** | **5,102,516** | **220** |
| Airbus Industrie A310-200c/F | 767,805 | 430 | 2,991,040 | 1,315,032 | 220 |
| Boeing 757-300 | 1,316,069 | 957 | 3,668,839 | 2,586,814 | 221 |
| Mcdonnell Douglas Dc-8-62 | 97,033 | 51 | 254,572 | 177,533 | 220 |
| Mcdonnell Douglas Dc-8-63f | 59,298 | 26 | 198,211 | 123,187 | 220 |
| Mcdonnell Douglas Dc-8-71 | 225,865 | 122 | 952,129 | 455,518 | 220 |
| Mcdonnell Douglas Dc-8-73 | 275,093 | 145 | 733,155 | 269,277 | 220 |
| Mcdonnell Douglas Dc-8-73f | 87,114 | 49 | 374,761 | 175,155 | 220 |
| **⊟250** | **11,872,878** | **7,169** | **34,830,244** | **22,871,327** | **248** |
| Airbus Industrie A300b/C/F-100/200 | 35,624 | 16 | 52,574 | 2,613 | 250 |
| Airbus Industrie A300-B2 | 287 | 0 | 1,990 | 732 | 250 |
| Boeing 767-300/300er | 11,775,727 | 7,131 | 34,602,080 | 22,764,069 | 239 |
| Lockheed L-1011-1/100/200 | 41,635 | 15 | 102,809 | 51,515 | 250 |
| Mcdonnell Douglas Dc-10-40 | 19,606 | 7 | 70,793 | 52,398 | 250 |
| **⊟275** | **7,311,708** | **3,614** | **22,302,795** | **13,783,256** | **272** |
| Airbus Industrie A300-600/R/Cf/Rcf | 2,938,942 | 1,554 | 11,174,746 | 5,465,594 | 267 |
| Boeing 767-400/Er | 2,313,675 | 1,243 | 5,973,817 | 4,604,816 | 268 |
| Lockheed L-1011-500 Tristar | 124,771 | 48 | 321,600 | 197,891 | 283 |
| Mcdonnell Douglas Dc-10-10 | 1,796,053 | 720 | 4,412,822 | 3,172,961 | 270 |
| Mcdonnell Douglas Dc-10-30cf | 138,266 | 50 | 419,810 | 341,994 | 270 |
| **⊟300** | **14,816,058** | **6,492** | **38,539,572** | **27,737,666** | **297** |
| Airbus A330-300 | 188,104 | 94 | 477,224 | 415,195 | 298 |
| Airbus Industrie A330-200 | 2,018,098 | 1,023 | 5,668,276 | 4,254,746 | 297 |
| Boeing 777-200/200lr/233lr | 10,143,473 | 4,478 | 26,442,390 | 19,446,111 | 289 |
| Mcdonnell Douglas Dc-10-30 | 2,466,383 | 897 | 5,951,682 | 3,621,614 | 304 |
| **⊟325** | **5,858,319** | **2,264** | **19,207,908** | **10,144,588** | **323** |
| Mcdonnell Douglas Md-11 | 5,858,319 | 2,264 | 19,207,908 | 10,144,588 | 323 |
| **⊟375** | **7,696,316** | **2,248** | **18,252,934** | **12,401,841** | **363** |
| Boeing 747-400 | 7,696,316 | 2,248 | 18,252,934 | 12,401,841 | 363 |
| **⊟400** | **1,280,344** | **344** | **2,963,303** | **2,059,435** | **400** |
| Boeing 747c | 28,366 | 10 | 121,403 | 65,763 | 400 |
| Boeing 747f | 1,251,978 | 335 | 2,841,900 | 1,993,672 | 400 |
| **⊟425** | **3,772,962** | **1,007** | **7,151,433** | **4,482,485** | **430** |
| Boeing 747-200/300 | 3,772,962 | 1,007 | 7,151,433 | 4,482,485 | 430 |
| **⊟450** | **791,882** | **202** | **1,586,896** | **1,201,277** | **452** |
| Boeing 747-100 | 791,882 | 202 | 1,586,896 | 1,201,277 | 452 |

The hourly air fuel consumption is calculated by dividing total air fuels issued for the aggregate aircraft class by the total air hours flown by the same seat class.

The hourly aircraft direct expenses not related to fuel consumption are calculated by subtracting total fuel costs from total direct operational costs for the aggregate aircraft class, then dividing this by the total air hours flown by the same seat class. These operational costs varied based upon the aircraft type.

**Table 21 ASOM cost factors and burn Rates aggregated by aircraft sizes for current aircraft**

| Aircraft Size | Gallons/Hr | non-fuel $/hr |
|---|---|---|
| **25** | 155 | $ 462 |
| **50** | 487 | $ 758 |
| **75** | 448 | $ 688 |
| **100** | 928 | $ 1,043 |
| **125** | 856 | $ 1,076 |
| **150** | 1005 | $ 1,174 |
| **175** | 1186 | $ 1,246 |
| **200** | not reported in BTS | |
| **225** | 1625 | $ 2,338 |
| **250** | 1727 | $ 1,736 |
| **275** | 2048 | $ 2,387 |
| **300** | 2305 | $ 1,681 |
| **325** | 2604 | $ 4,029 |
| **350** | not reported in BTS | |
| **375** | 3537 | $ 2,689 |
| **400** | 3741 | $ 2,535 |
| **425** | 3704 | $ 2,620 |
| **450** | 3910 | $ 1,904 |

The current aircraft reported in the BTS P52 database do not reveal smooth curves when plotting direct operation costs minus fuel and aviation fuel burn rates per seat, as shown in Figure 19 and Figure 20. This was an important observation of the input data for the ASOM model since the model will be maximizing profit by subtracting direct costs from revenue.  Early runs of the ASOM model showed the model did not like to choose the 50 or 100 seat classes in the schedules, where historically these sized aircraft are flown.  Since the burn rates for these classes are much higher than their neighboring seat classes these flight options were typically avoided.  These cost factors and burn rates are used in the current aircraft scenarios.  The ASOM does not force an airline to use its current fleet but rather allows it to up gauge or down gauge to more efficient aircraft.  This is both a limitation and a capability of the model.  The model instructs the aviation industry what economic advantages exist for aircraft purchases, without the higher capital costs considered.

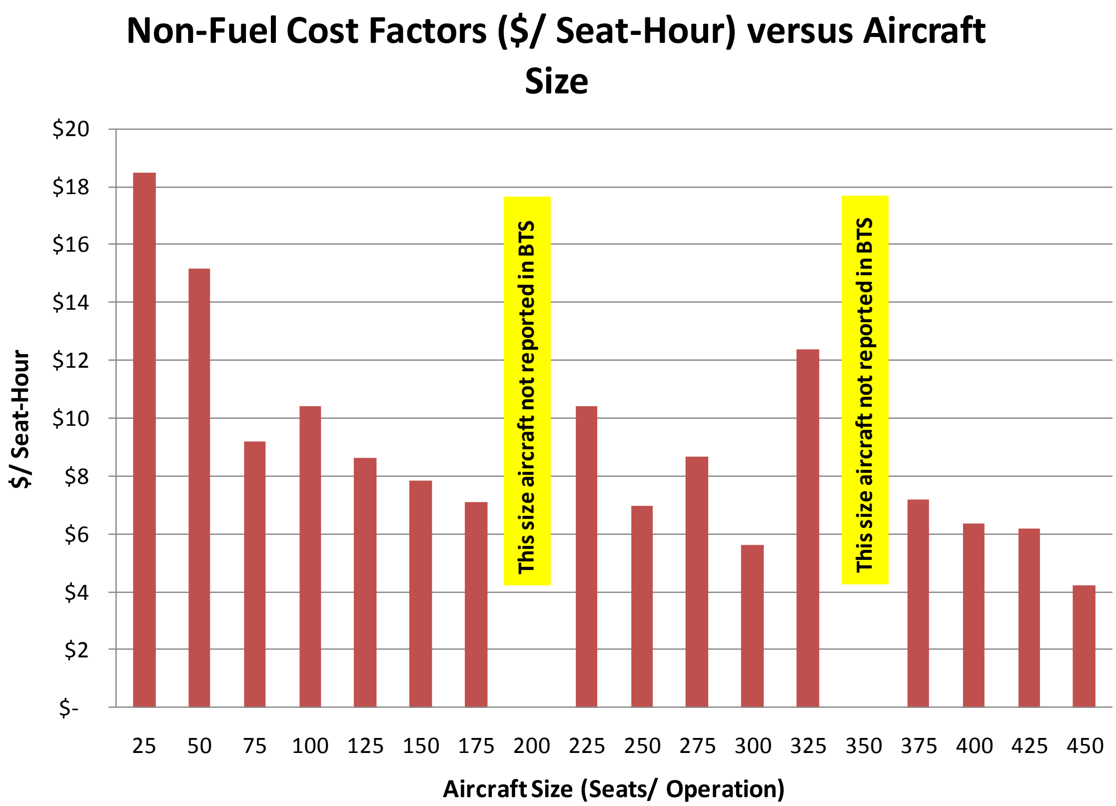



**Figure 19 Current BTS P52 non-fuel costs per seat-hour**

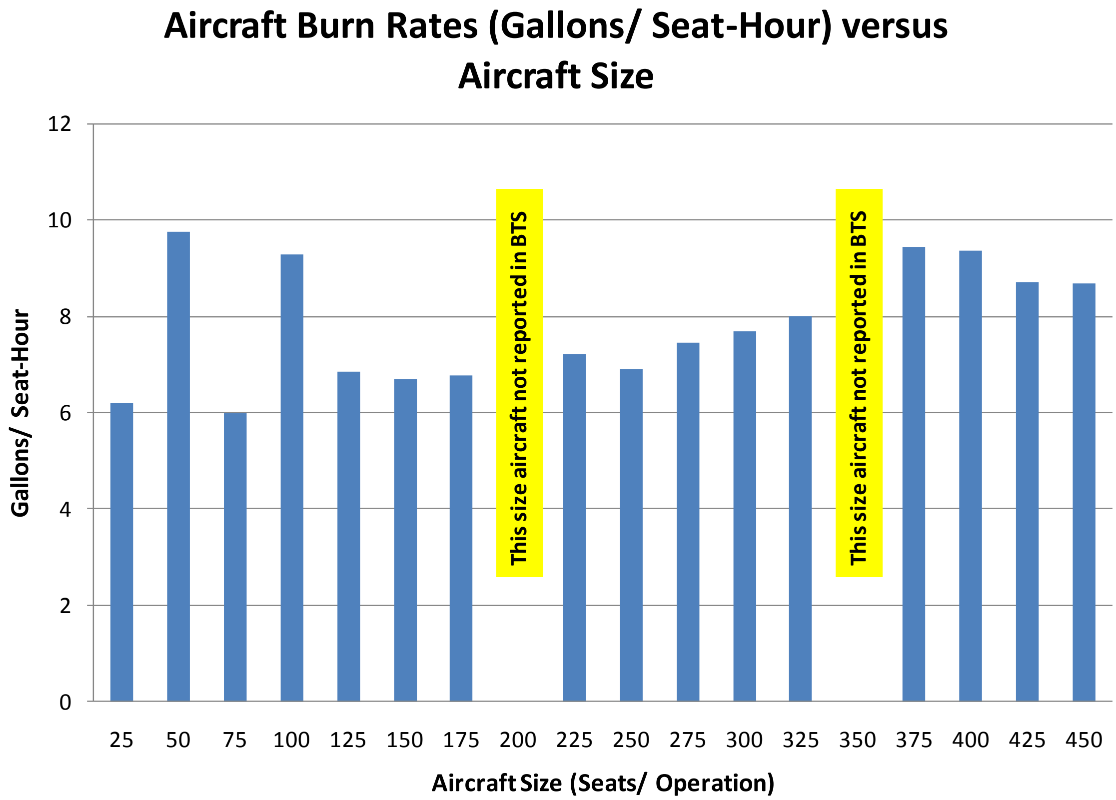



**Figure 20 Current BTS P52 gallons per seat-hour**

The flight costs for markets are derived by multiplying the average scheduled flights times from the FAA ASPM database by the aircraft respective cost factors, burn rates and fuel costs as shown below.

Market flight costs = (Direct $/ hr + (Gallons/ hr x Fuel Price) x avg scheduled block times + landing fees

**Equation 15 ASOM market flight cost**

The landing fees applied in the ASOM are shown below in Table 22.

**Table 22 ASOM landing fees**

| Class | Avg Weight | Avg Seats | landing fee | $/ seat-landing |
|---|---|---|---|---|
| 25 | 39 | 26 | $ 112 | $ 4.25 |
| 50 | 48 | 50 | $ 137 | $ 2.74 |
| 75 | 76 | 76 | $ 218 | $ 2.86 |
| 100 | 116 | 103 | $ 330 | $ 3.21 |
| 125 | 125 | 124 | $ 356 | $ 2.86 |
| 150 | 129 | 147 | $ 367 | $ 2.49 |
| 175 | 241 | 168 | $ 686 | $ 4.09 |
| 200 | 192 | 204 | $ 546 | $ 2.68 |
| 225 | 332 | 220 | $ 945 | $ 4.30 |
| 250 | 317 | 250 | $ 904 | $ 3.61 |
| 275 | 373 | 270 | $ 1,062 | $ 3.93 |
| 300 | 460 | 305 | $ 1,312 | $ 4.30 |
| 325 | 498 | 327 | $ 1,421 | $ 4.33 |
| 350 | 537 | 350 | $ 1,530 | $ 4.37 |
| 375 | 575 | 372 | $ 1,640 | $ 4.40 |
| 400 | 614 | 394 | $ 1,749 | $ 4.43 |
| 425 | 652 | 416 | $ 1,859 | $ 4.47 |
| 450 | 585 | 452 | $ 1,668 | $ 3.69 |

## 4.3. Airport Schedule Optimization Model (ASOM) Equilibrium Model

An equilibrium model is used to determine the most profitable schedule. First a collection of feasible schedules is generated for each market and based on these schedules a "master problem" is solved that chooses among these schedules an overall schedule for the airport. The master problem consists of constraints that limit the number of arrivals and departures into the airport during each 15-minute period. Thus, the dual prices that are output to the optimization model measure the value of an additional flight within any time period. This shadow price information is used to calculate new schedules for each market. Thus, for each market, new schedules were collected based using as objective function costs, the shadow prices. All schedules that are profitable with these costs are again fed to the master problem. A further explanation is provided when we discuss in detail the sub-problems.

The master-problem again determines an optimal airport schedule by selecting market schedules that maximizes profit for the airport within the operational capacity of the airport. The process iterates between the solution of the master problem and the generation of new market schedules until no such new schedules improves the master problem. This overall approach is called “Column Generation.”

This process continues until either there is no improvement in the total profit (objective function) or no new schedules are generated. Once the problem is solved to linear optimality, if the solution obtained is not integer, a tree search is invoked to prove integer optimality using the same column-generation approach on each branch of the tree, see Figure 21 below.

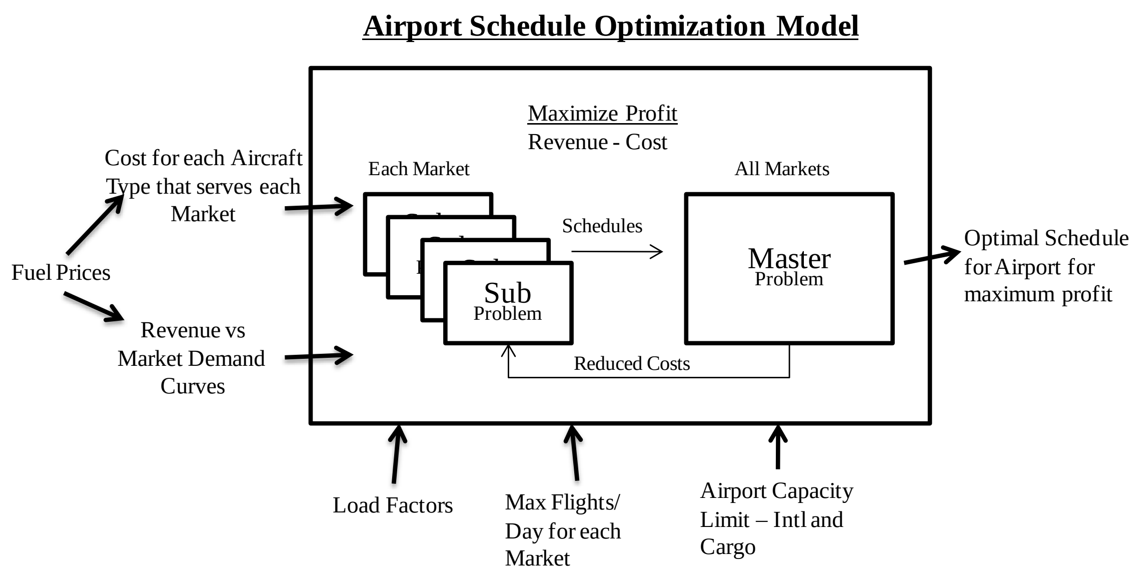



**Figure 21   ASOM interactions between master and sub problems**

Figure 22 shows from a fundamental standpoint the ASOM sub-problem generates optimum market flights schedules are shown in the middle column of the figure from revenue versus demand curves shown in the first column for all 15 minute periods. The market schedules must be chosen to assure that the overall schedule does not exceed runway capacity at any given 15 minute period of the day.

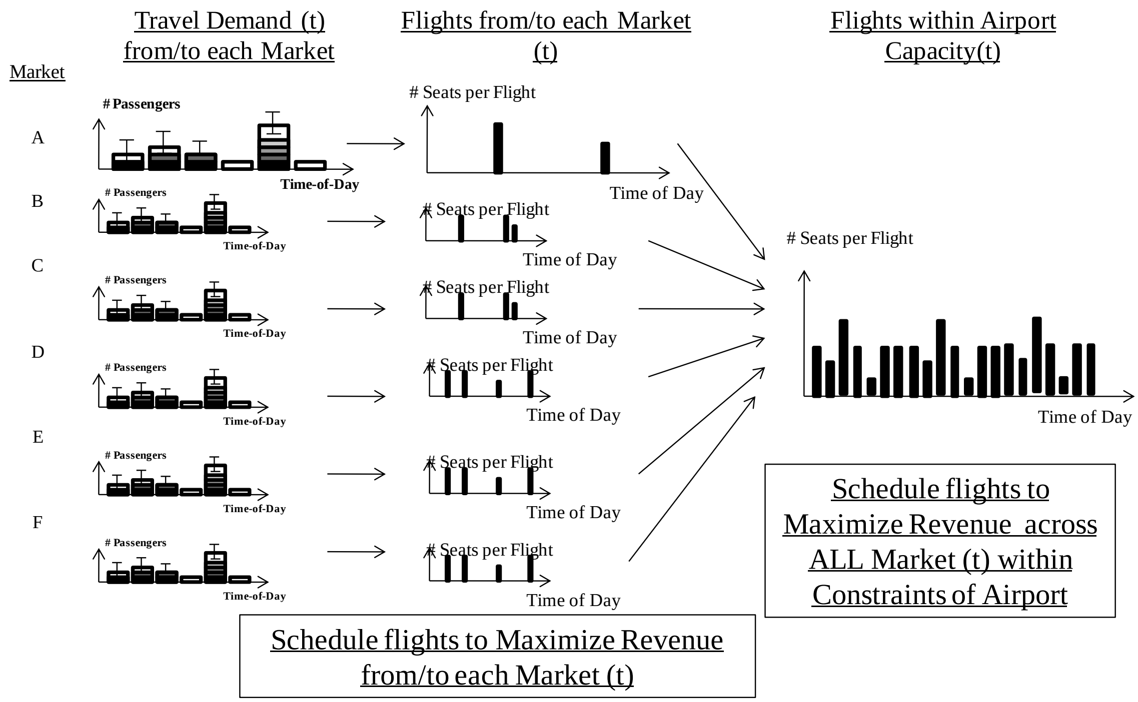



**Figure 22 ASOM process of allocating historic market demand by time of day on flights and then fitting these flights into an airport daily schedule**

### 4.3.1. ASOM Scope and Assumptions

The ASOM generates profitable schedules for non-stop daily domestic markets. The schedules allow only one flight per 15 minute period to or from each market. The domestic markets are not static but compete for the airport's capacity.

Aircraft that have historically been used for domestic flights are grouped into fleet classes at increments of 25 seats. For example, aircraft between 88 seats and 112 seats would be in the 100 seat fleet class as shown in Table 23. Table 23 shows, for all domestic flights in the US from 2005 to 2010, 90.42% of the passengers flown and

79.92% of the departures were performed using only six fleet classes. Since the ASOM selects only aircraft for each market's schedule based on aircraft historically flown to each market, the model will be for the most part choosing between these seven fleet classes to determine the most profitable aircraft class to meet the demand.

**Table 23 Summary of seat-capacity grouping of aircraft historically used for domestic operations**

| Fleet Class | # of Aircraft types | seat range | % Departures | % Passengers |
|---|---|---|---|---|
| 0 | 42 | <13 | 5.27% | 0.24% |
| 25 | 17 | 13 - 37 | 11.59% | 2.91% |
| 50 | 6 | 38 - 62 | 24.79% | 12.65% |
| 75 | 11 | 63 - 87 | 8.59% | 6.55% |
| 100 | 4 | 88 - 112 | 1.65% | 1.72% |
| 125 | 9 | 113 - 137 | 24.59% | 32.81% |
| 150 | 6 | 138 - 162 | 16.14% | 26.24% |
| 175 | 4 | 163 - 187 | 5.78% | 12.18% |
| 200 | | 188 - 212 | 0.00% | 0.00% |
| 225 | 1 | 213 - 237 | 0.39% | 1.06% |
| 250 | 1 | 238 - 262 | 0.74% | 2.14% |
| 275 | 10 | 263 - 287 | 0.43% | 1.37% |
| 300 | 2 | 288 - 312 | 0.01% | 0.04% |
| 325 | | 313 - 337 | 0.00% | 0.00% |
| 350 | 1 | 338 - 362 | 0.00% | 0.00% |
| 375 | 1 | 363 - 387 | 0.03% | 0.09% |
| 400 | 1 | 388 - 412 | 0.00% | 0.00% |
| 425 | | 413 - 437 | 0.00% | 0.00% |
| 450 | 1 | 438 - 462 | 0.00% | 0.00% |

Flight demand is not captured at the 15 min level of fidelity in the historical data. We therefore infer market demand by time of day based on data that is available: namely, the supply (seats) as announced in the published schedule by time of day. We assume that the aircraft in that published schedule has a load factor of 80% and from that published schedule infer the market demand. The optimization model will take this information along with demand curves at various price points (elasticity data) and determine the size of aircraft to use for each flight. The model allows demand to spill into different time slots, but restricts demand from moving between mornings, afternoon, or evening time periods. This is done by nesting demand into 3 periods (12am-12pm, 12pm-5pm and 5pm-12am). The nesting also ensures that the over the 15 minutes demand periods does not exceed the demand from the morning, afternoon or evening total demand.

The ASOM assumes that the price/demand data provided in the BTS DB1B database is representative and is a good model of the price sensitivity that exists in that market.

When such an airline is “benevolent” it posts prices that are consistent with current competitive prices (i.e. it does not seek monopolistic rents) and attempts to serve as many markets as it can, while remaining profitable. The quarterly historical passenger demand versus airfare relationship is assumed consistent over the period studied as the ASOM provides a daily schedule. However, this passenger demand is adjusted for economic conditions and operational costs as discussed in Chapter 3.

The ASOM builds the network of potential flights based on arrivals from the cluster airport to the direct non-stop market airport. The ASOM then assumes a 45 minute turnaround time for all fleets before a departure is allowed back to the cluster airport.

Since the databases used do not include all airlines, the ASOM assumes that the data from reporting carriers is representative of behavior from all carriers.

### 4.3.2. ASOM Limitations

The ASOM models exhibits the following limitations:

1. The ASOM model considers airline scheduling decision strictly based on operational profitability rather than any decisions that are made for strategic positioning. It does not model airline competition, except as it uses pricing curves that are based on competitive behavior.

2. The ASOM models chooses only profitable markets to serve and does not consider staying in unprofitable markets during down economic times in order to retain market share. Thus, the model is likely to move out of markets more quickly than might actually occur during recessionary periods.

3. The ASOM models how the airline industry as a whole is serving these profitable markets, which finds the optimal schedule minus airline competition by modeling the problem as if the industry were a single airline. For the analysis of EWR and SFO (hubs for large carriers), this assumption may be closer to actual behavior than at airports such as LGA where there is significant demand and competition at the airport.

4. The ASOM model balances arrivals and departures and does not model the advantages of banking (i.e. having many incoming flights during one period that would

allow passengers to connect to other flights during the next few periods). Such banking would require the Traffic Flow Management system to change arrival and departure capacities on runways for 15 minute segments or queues would develop. To have banking work well runway capacity would need to be reduced to alleviate queue build ups at the airport.

5. The model also tries to satisfy the demand based on historic data. Thus, it does not allow demand from the morning to spill into the afternoon.

6. Because the ASOM model aggregates the airline industry into a single airline, it exhibits the following limitations:

- The model reflects airline behavior from an operational rather than a strategic viewpoint and therefore does not consider remaining in markets that prove unprofitable in order to maintain market share.
- The ASOM model does not model actions taken for reasons of competition. This aggregated airline does not concern itself with frequency of market share. For example, this single airline model will choose to use a larger aircraft in shuttle markets rather than have (as is currently the case) eight departures from LGA to DCA in a single hour.
- The ASOM model balances airport arrivals and departures for each 15 minute period and does not consider how banking might allow more connections to take place.

7. Aggregate airline responses to economic or policy changes will vary depending on the airport characteristics. The differences can be explained by the different markets these airports serve, the different airlines which operate these airports and the different levels of competition which exist at these airports.

### 4.3.3. ASOM Flight and Ground Arcs

A “time-space” network is built to represent all feasible flights to and from the daily markets during the day. Flights are allowed to depart or arrive at the modeled airport and market airports between 5:15 and 24:00 local time. The average scheduled flight times are calculated using the FAA ASPM database. A 45 minute minimum turnaround time is allowed between flight arcs although flights can remain on the ground for longer.

The flight arcs are matched up with the ground arcs to allow for the ASOM to decide when and if to fly specific flights. These ground arcs also allow for the ASOM to model over-night operations. Figure 23 is an example of the timeline network for a city pair that has the same time zone. The figure constructs the flight arcs for fleet 1 that requires 1.5 time windows for flight time in both directions, and 0.5 time window for minimum turnaround time. Flight arcs for fleet 2 are also shown that needs 2.5 time windows for flight time in different directions and 0.5 time window for minimum turnaround time. The sub-networks for all valid fleets put together a multi-commodity flow timeline network for the city pair.

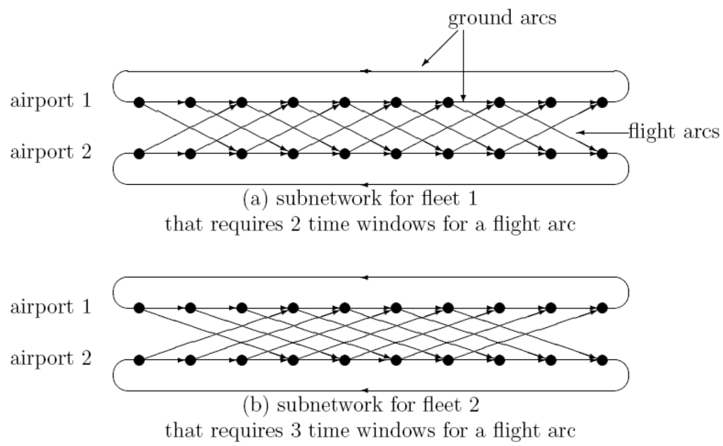



**Figure 23 Example of flight arcs and ground arcs for two different fleet classes**

### 4.3.4. Interaction of Demand and Supply through Price

In microeconomics, it is well known that demand and supply interact through price. The law of demand states that given other things remaining the same, the higher the price of a good, the smaller is the quantity demanded. This same relationship is performed in the ASOM based on the demand versus airfare curves that will be discussed in this section. Therefore when the ASOM changes fleet sizes demand served for the market for the 15 minute time window will be proportionally change, which will simultaneously adjust airfares and revenue accordingly in accordance with these demand curves.

Data representing passenger behavior of demand versus airfares can be found in the Bureau of Transportation Statistics (BTS) Airline Origin and Destination Survey (DB1B) database. (U.S. DOT/BTS 2010) The DB1B database is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the Bureau of Transportation Statistics. Data includes origin, destination and other itinerary details of passengers transported. This database is used to determine air traffic patterns, air carrier market shares and passenger flows. For the ASOM this database will be used to derive passenger demand versus revenue curves discussed earlier. The first step of this process is to estimate passenger demand versus airfare curves for each market; this process is discussed in more detail in chapter 3.

The quarterly demand versus airfare data from the DB1B data are normalized to represent average daily market demand by multiplying by the ratio of BTS T100 daily demand over the BTS DB1B quarterly demand by the BTS DB1B quarterly demand for each airfare examined. This data is then fit into an exponential representation of passenger demand versus airfare, to derive intercept and slope coefficients from the log-linear regression fit of the data, as shown in Equation 16.

$$Demand = (Demand\_Coeff) * e^{price\_coeff*airfare}$$

**Equation 16 ASOM log-linear demand model (exponential demand versus airfare)**

In chapter 3 of this dissertation, coefficients were derived to adjust passenger price elasticity and passenger demand to reflect changes in fuel price. Demand coefficients are decayed 0.52% (adj R2 = .54) for each $1 increase in hedged fuel prices. Price coefficients are decayed 12.59% (adj R2 = .367) for each $1 increase in hedged fuel prices. These decay rates are applied to the individual market demand versus revenue curves to capture the effects of fuel prices changes.

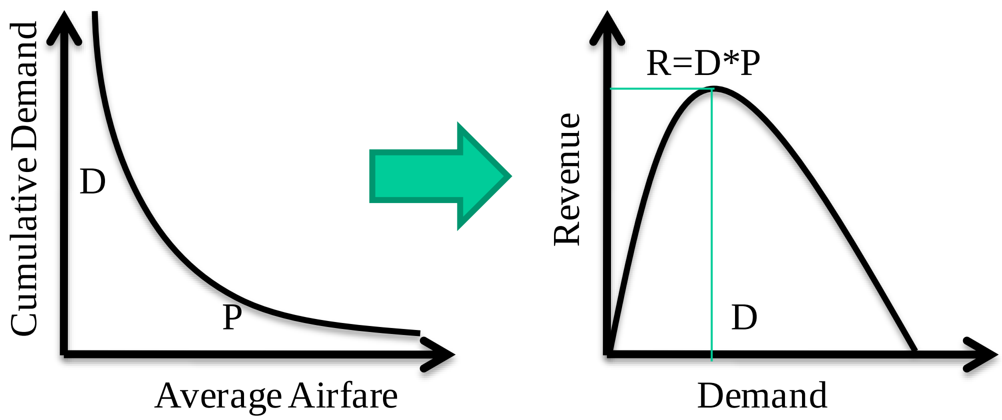



**Figure 24 Transforming cumulative demand versus average airfare curves into revenue versus demand curves**

The next step is to adjust these curves so that they can be used within a linear-integer optimization problem. The ASOM models a single aggregate airline that is profit seeking, therefore these cumulative demand versus average airfare curves must be converted into revenue versus demand curves, as shown in Figure 24. To solve for airfare the natural logarithm of both sides of Equation 16 is taken as shown in Equation 17 and Equation 18 below. Next Revenue can be solved by multiplying demand by airfare as shown in Equation 19.

$$Ln(Demand) = Ln(Demand\_Coeff) + price\_coeff * airfare$$

**Equation 17 ASOM log-linear demand model (simplified by taking the log of both sides of the equation)**

$$airfare = \frac{Ln(Demand) - Ln(Demand\_Coeff)}{price\_coeff}$$

**Equation 18 ASOM log-linear demand model (solved for airfare)**

$$\mathrm{Re}venue = Demand * airfare = Demand * \frac{Ln(Demand) - Ln(Demand\_Coeff)}{price\_coeff}$$

**Equation 19 Revenue formula for the ASOM log-linear demand model**

The next step is to adjust these curves so that they can be used within a linear-integer optimization problem. Since the curves are non-linear, we take piecewise-linear approximations to the curves and use special-ordered-sets of type 2 to assure that the optimization correctly interpolates between these piecewise segments (see Wolsey, 2005 for more on piecewise linear approximations). Since demand is time of day sensitive piecewise segments are generated for departure and arrival 15 minute windows where historic flights were historically flown as reported in the ASPM database. For these 15-minute piecewise segments the revenue is normalized by the ratio of seats flown on average during the 15-minute time window divided by the average daily seats flown for the market as shown in Equation 20. This process ensures all time windows will achieve maximum revenue at the same airfare.

$$\mathrm{Re}venue = Demand * \frac{15\min seats}{daily\_seats} * \frac{Ln(Demand) - Ln(Demand\_Coeff)}{price\_coeff}$$

**Equation 20 15-min revenue formula for the ASOM log-linear demand model**

A similar process is followed to generate piecewise segments for revenue versus demand curves for three periods during the day (6:00am to 12:00pm, 12:01pm to 17:00pm, and 17:01pm to 24:00pm). The revenue is normalized by the ratio of seats flown on average during the period time window divided by the average daily seats flown for the market as shown in Equation 21. The 15-minute time windows are allowed to spill demand into each other as long as the sum of the revenues and demands for the 15 minute periods in a period do not exceed the revenue or demand for that period. This relationship is called nesting. Therefore, demand might be spilled from one time window to another, but not between time periods during the day.

$$\mathrm{Re}venue = Demand * \frac{period\_seats}{daily\_seats} * \frac{Ln(Demand) - Ln(Demand\_Coeff)}{price\_coeff}$$

**Equation 21  15-min revenue formula for the ASOM log-linear demand model**

Through the testing of the model, we have concluded that increasing the number of segments used in the approximation provides little improvement to the solution value, but greatly increases the ASOM's run time.  The revenue for these piecewise segments are plotted into equal demand intervals from zero demand to four times the average historic demand, because this range typically reflects the entire positive range for revenue.  This also ensures that flights could be up gauged as well as down gauged and to ensure the most profitable choices were available for the ASOM to choose from.

For each of these data points the demand is plugged back into the fitted exponential demand versus airfare formula, with adjusted coefficients based upon changes in fuel prices as shown below.

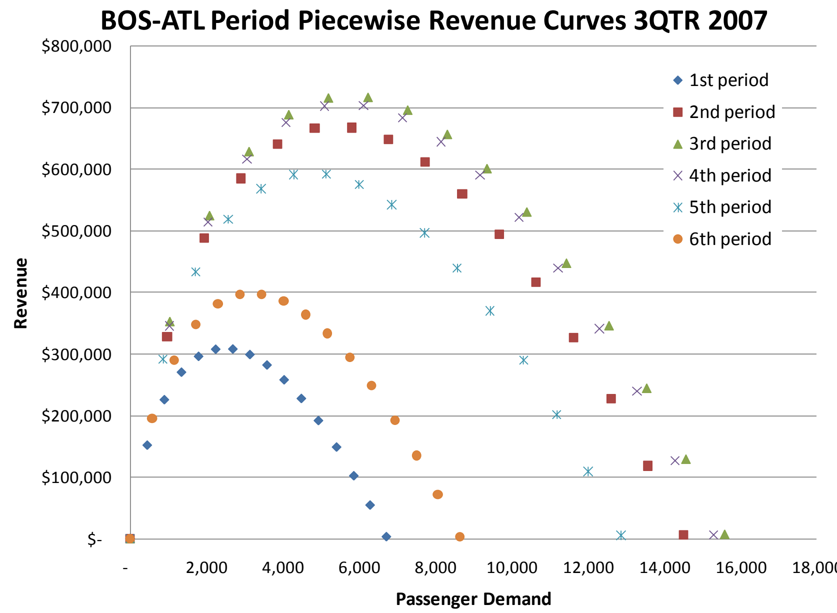



**Figure 25 BOS-ATL period revenue versus demand curves 3QTR 2007**

Figure 25 shows an example of derived period revenue versus demand curves for the BOS-ATL market. Periods 4-6 represent periods for arrivals at the market, ATL in this case. Similar curves are generated for all 15 minute time windows with historic flights.

As discussed earlier, we take piecewise approximation to these curves so that we can use linear-integer optimization software to solve the problem. The ASOM imposes integrality constraints that restrict the interpolation to take place only between adjacent approximation points. This makes the market sub-problem formulation a mixed integer problem (MIP).

### 4.3.5. ASOM Airport Master-Problem

The inputs for the Master

The master problem is presented in the Figure 26. This problem is solved as a set packing problem for the potential market schedules generated constrained by airport capacity, with no more than one schedule chosen per market. The objective function maximizes total profit for the airport's schedule.

Sets are as follows:

$M$ = Set of possible markets

$S$ = Set of schedules submitted to master problem from sub problems

$S(m)$ = Set of schedules for market $m$

$T$ = Set of 15 minute time windows in the day

Data are as follows:

$Z_j$ = Profit from schedule j

$a_{ij}$ = 1 if there is an arrival in schedule j at time period i, otherwise $a_{ij}$ = 0

$d_{ij}$ = 1 if there is an departure in schedule j at time period i, otherwise $d_{ij}$ = 0

$I_j^a$ = average number of international or cargo arrivals for time i

$I_j^d$ = average number of international or cargo departures for time i

$C_i$ = arrival/departure rates of time window i

Variables are as follows:

$y_j$ = 1 if schedule j is selected, otherwise $y_j$ = 0

$$\max \sum_{j \in S} Z_j y_j \tag{1}$$

subject to

$$\sum_{j \in S} a_{ij} y_j \leq C_i - I_i^a \quad \forall i \in \mathcal{T} \tag{2}$$

$$\sum_{j \in S} d_{ij} y_j \leq C_i - I_i^d \quad \forall i \in \mathcal{T} \tag{3}$$

$$\sum_{j \in S(m)} y_j \leq 1 \quad \forall m \in \mathcal{M} \tag{4}$$

$$y \in B^{|S|}$$

**Figure 26  ASOM master problem**

Figure 26 shows the formulation of the ASOM master problem. The objective is to maximize the profit for the airport (1). Constraint sets (2) and (3) ensure that there are no more flights in a single 15-minute bin than the arrival and departure capacity available to handle these flights, respectively. Capacity is defined to be airport capacity minus the portion of that capacity used by international and cargo flights. Constraint set (4) guarantees that at most one schedule per market pair is chosen.

### 4.3.6. ASOM Market Sub-Problems

The ASOM sub-problems are solved as multi-commodity flow network problem. The sub problem is presented below. The objective function maximizes total profit for the markets schedule from the airport.

Indexed sets are as follows:

$\boldsymbol{T}$ = Set time windows in the day.

$\boldsymbol{K}$ = Set of aircraft types historically flown between the two airports of the market.

$\boldsymbol{A^F}$ = Set of flight arcs

$\boldsymbol{Q(i)}$ = Set of linear segment indexes for the revenue function of $\boldsymbol{i} \in \boldsymbol{T}$

Input data are includes:

$\boldsymbol{R_{iq}}$ = Linear segment revenue for time $i$ and segment $q$

$\boldsymbol{A_{iq}}$ = Linear segment passenger demand for time $i$ and segment $q$

$\boldsymbol{C^k_{ij}}$ = Direct operating cost for one flight of fleet type $k$ for flight arc $(i,j)$

$\boldsymbol{l}$ = Average load factor

$\boldsymbol{S^k}$ = Number of seats available on an aircraft of fleet type $k$

Variables are as follows:

$\beta_{pr}$ = Decision variable (0,1) for period *r* and segment *p*

$\lambda_{iq}$ = Decision variable (0,1) for time *i* and segment *q*

$x^k_{ij}$ = Decision variable (0,1) for one flight of fleet type *k* for flight arc (*i*,*j*)

$$\max\ z = \sum_{i\in\mathcal{T}} \sum_{q\in\mathcal{Q}(i)} R_{iq}\lambda_{iq} - \sum_{(j,i)\in\mathcal{A}^F} \sum_{k\in\mathcal{K}} C^k_{ji} x^k_{ji} \tag{5}$$

$$\text{subject to} \sum_{(j,i)\in\mathcal{A}^F} x^k_{ji} - \sum_{(i,j)\in\mathcal{A}^F} x^k_{ij} = 0 \quad k\in\mathcal{K} \tag{6}$$

$$l\sum_{k\in\mathcal{K}} \sum_{(j,i)\in\mathcal{A}^F} S^k x^k_{ji} - \sum_{q\in\mathcal{Q}(i)} A_{iq}\lambda_{iq} = 0 \quad \forall i\in\mathcal{T} \tag{7}$$

$$\sum_{i\in\mathcal{E}(p)} \sum_{q\in\mathcal{Q}(i)} A_{iq}\lambda_{iq} - \sum_{r\in\mathcal{Q}(p)} A_{pr}\beta_{pr} = 0 \quad \forall p\in\mathcal{P} \tag{8}$$

$$\sum_{i\in\mathcal{E}(p)} \sum_{q\in\mathcal{Q}(i)} R_{iq}\lambda_{iq} - \sum_{r\in\mathcal{Q}(p)} R_{pr}\beta_{pr} \le 0 \quad \forall p\in\mathcal{P} \tag{9}$$

$$\sum_{k\in\mathcal{K}} \left( \sum_{(i,j)\in\mathcal{A}^F} x^k_{ij} + \sum_{(j,i)\in\mathcal{A}^F} x^k_{ji} \right) \le max\_freq + 1 \tag{10}$$

$$\sum_{k\in\mathcal{K}} \sum_{(j,i)\in\mathcal{A}^F} S^k x^k_{ji} - IntDem \ge 0 \tag{11}$$

$$\sum_{k\in\mathcal{K}} \sum_{j\in\mathcal{T}} x^k_{ij} \le 1 \quad \forall i\in\mathcal{T} \tag{12}$$

$$\sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{T}} x^k_{ij} \le 1 \quad \forall j\in\mathcal{T} \tag{13}$$

$$\sum_{q\in\mathcal{Q}(i)} \lambda_{iq} = 1 \quad \forall i\in\mathcal{T} \tag{14}$$

$$\sum_{r\in\mathcal{Q}(p)} \beta_{pr} = 1 \quad \forall p\in\mathcal{P} \tag{15}$$

$$x^k_{ij} \in B_+^{|\mathcal{A}^F|\times|\mathcal{K}|}, \lambda_{iq} \in R_+^{|\mathcal{T}|\times|\mathcal{Q}(i)|}, \beta_{pr} \in R_+^{|\mathcal{P}|\times|\mathcal{Q}(p)|}$$

**Figure 27 ASOM multi-commodity flow network sub problem**

The formulation of the ASOM sub problem maximizes the profit for a market serving the airport, as shown in (5) where we calculate the revenue based on piece-wise linear approximations to the demand curve and subtract off the operating costs,.

Constraint set (6) are flow balance constraints that assure that, for each fleet type, there is an equal number of incoming and outgoing aircraft of that type. It also assures that an aircraft must arrive before it can depart and it must remain of the same type.

Constraint set (7) assures that there is sufficient supply for the demand given that the aircraft will not be chosen if it cannot fill at least 80% of the seats.

Constraint sets (8) and (9) assure that two piecewise segments $\lambda_{iq}$ are chosen to approximate the revenue and demand of the flight for time i. These constraints also ensure that revenue from all of flights in the period does not exceed the revenue calculated from the piecewise segments $\beta_{pr}$. As previously discussed, this relationship is called nesting. Therefore, demand might be spilled from one time window to another, but not between time periods during the day.

Constraint set (10) requires the number of flights into a market is approximately equal to the number of flights out of a market (can differ by no more than one) and that the total flights into the market does not exceed the maximum frequency to that market.

Constraint set (11) ensures that international passenger demand that is connecting from domestic markets is satisfied. Therefore, we will not eliminate an unprofitable market which connects domestic passengers to international flights.

Constraints sets (12) and (13) ensure that there is only one flight between the market pair in the same time window.

Constraint sets (14) and (15) ensures that only one segment of the piecewise linear approximation for the revenue curve is chosen for each time window and period respectively. One does not need adjacent weight restrictions (see Wolsey 2005) for more on special-ordered sets of type 2) because the optimization model is maximizing profit and the revenue versus demand curve approximations are concave.

### 4.3.7. ASOM Output files

There are two text files created by the model for each run. A sample log file is generated that details each new schedule that is generated in the sub problem. It also provides the number of iterations between master and sub-problems. Lastly, the expected profit from the final airport's schedule is shown.

The second output file is the schedule file, Figure 28. This file provides the individual flights at each market that are in the airport's final schedule. For each flight or row of data the market served, the size of aircraft, the departure time, the arrival time, the cost of the flight, and the passenger ticket revenue. The average ticket price per flight can be derived by dividing the passenger ticket revenue by the number of seats on the aircraft and the average load factor for the market.

| Market | Size | Dep Time | Arr Time | Freq |
|---|---|---|---|---|
| ABE | 6 | 76 | 178 | 1.0 |
| ABE | 6 | 176 | 86 | 1.0 |
| ACK | 2 | 39 | 143 | 1.0 |
| ACK | 2 | 123 | 35 | 1.0 |
| …… | | | | |
| TYS | 3 | 73 | 180 | 1.0 |
| TYS | 3 | 152 | 67 | 1.0 |

| Market | Fleet si | i | j | freq | local ti | seats | year | qtr | airport | cap | fp | dist | ASM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABE | 6 | 76 | 178 | 1 | 76 | 150 | 2009 | 3 | EWR | 9 | 8 | 67 | 10050 |
| ABE | 6 | 176 | 86 | 1 | 86 | 150 | 2009 | 3 | EWR | 9 | 8 | 67 | 10050 |
| ACK | 2 | 39 | 143 | 1 | 39 | 50 | 2009 | 3 | EWR | 9 | 8 | 218 | 10900 |
| ACK | 2 | 123 | 35 | 1 | 35 | 50 | 2009 | 3 | EWR | 9 | 8 | 218 | 10900 |
| ALB | 3 | 26 | 130 | 1 | 26 | 75 | 2009 | 3 | EWR | 9 | 8 | 143 | 10725 |

| | | | | |
|---|---|---|---|---|
| Comment | profit & fleet #2 | | | |
| airport | EWR | | | |
| year | 2009 | | | |
| cap | 12 | | | |
| fp | 8 | | | |
| | | | | |
| | **Values** | | | |
| **Row Labels** | **Sum of ASM** | **Sum of seats** | **Sum of freq** | Average Size |
| ATL | 6518750 | 8750 | 42 | |
| **Grand Total** | **99574150** | **94350** | **628** | 150.24 |

**Figure 28 ASOM schedule file**

The aircraft sizes are grouped into classes in 25 seat intervals, so to determine the class on needs to multiply the size by 25 seats, for example the first row identifies a size 6*25 = 150 seat aircraft.

The departure and arrival times are shown in 15 min intervals starting with 1 or 12:15am. The arrival or departure time which is less than 96 (there are 96 15-minute intervals in a 24-hour day) determines whether this is an arrival or departure from our modeled airport. To determine the arrival or departure time at the other airport subtract 96 from its number. For example the first row shows a departure from our airport to ABE at 76 (1900 hrs or 7:00pm) and this flight arrives at ABE at 178-96 = 82 (2030hrs or 8:30pm ABE local time). All times reported in the schedule are local times.

This schedule data from ASOM can be copied into a spreadsheet program to generate charts and tables and compare different scenarios based on different input parameters.

### 4.4. Airport Schedule Optimization Model (ASOM) Improvements and Contributions

The ASOM was improved from Le's original model by improving the pre-processing; modifying the formulation of the master and sub problems to account for international passengers and flights; and modifying the ASOM outputs to enable analyses of costs, revenue, and average ticket prices. The ASOM was also modified to allow for analysis of non-historical economic scenarios. Lastly the model was modified to enable analysis of different aircraft performance (current, modern, and best in class).

Fitting the average airfare versus demand curves to the semi-log demand function for all markets and directly computing the revenue versus demand curves from this formulation significantly sped up the ASOM preprocessing algorithms. The development of a price elasticity model to incorporate changes in economic conditions enables the ASOM to evaluate non-historical scenarios and to perform sensitivity analysis of airline metrics compared to increasing fuel prices.

Since it is a rare event for a market serving an airport to have more than 1 arrival or 1 departure in a 15 minute time period, the ASOM formulation was changed to allow only one arrival and one departure for each market for each 15 minute period of time. This improvement simplified the formulation and significantly sped up the ASOM model.

Le's original model was designed to analyze La Guardia Airport, which is predominately an airport with domestic non-stop direct markets. The ASOM's formulation was changed to account for international passengers and flights. Since domestic passengers connect from or to international flights at many US airports, the model's constrains were adjusted to ensure each domestic market's average daily domestic passengers to or from international markets would be served in the ASOM schedule even if the airline had to take a loss, see constraint 11 of the sub problem. Since the ASOM optimizes domestic schedules for an airport and many airports have significant daily cargo and international flights, the master problem was adjusted to reserve slots in the schedule for these operations. These improvements have the ASOM model to more accurately represent the domestic scheduling process.

Finally, the ASOM's output reporting capability for schedules was improved to provide costs, revenue and the ability to derive average ticket prices for each flight in the schedule.  This adjustment allows the ASOM to evaluate the average airfares for each of the flights in the schedule.

### 4.5. Airport Schedule Optimization Model (ASOM) Validation

The ASOM historically based optimization runs are compared to historic airline daily schedules for the airport.  Historic data can be compared to data from the ASOM for $2 fuel prices and VFR runway capacities, since there is historical data for third quarter 2007 from the eight airports in this study for operations run at or near VFR runway capacities.  This analysis will show how close the ASOM aggregate airline schedules flights and sets airfares relative to those actually operated out of the eight airports in third quarter 2007.

Figure 29 (a) shows the historic daily markets served, frequency of service, passenger demand and average airfare, average aircraft size and daily available seat miles for the eight airports examined.  Figure 29 (b) shows the same historic statistics for the markets in 3$^{rd}$ Quarter 2007, where the ASOM found profitable schedules.  Figure 29 (c) shows the same statistics for the markets in the ASOM profitable schedules.  Lastly Figure 29 (d) shows the ratio of ASOM data over historic data (c/b) for the profitable markets.

**Historic Baseline** **(a)**

| | 3QTR 2007 Baseline Statistics | | | | | |
|---|---|---|---|---|---|---|
| | Geographic Access | | Economic Access | | ATS Efficiency | |
| | Markets | Flights | Demand | Avg Airfare | Avg Aircraft Size | Daily ASMs (M) |
| BOS | 78 | 881 | 69,760 | $ 152 | 99 | 84 |
| DFW | 123 | 1,660 | 149,449 | $ 133 | 112 | 162 |
| EWR | 89 | 900 | 73,587 | $ 166 | 102 | 103 |
| JFK | 60 | 785 | 72,998 | $ 166 | 116 | 117 |
| LGA | 71 | 997 | 69,507 | $ 134 | 94 | 65 |
| PHL | 141 | 2,251 | 180,758 | $ 136 | 97 | 194 |
| ORD | 88 | 1,146 | 83,084 | $ 126 | 96 | 88 |
| SFO | 62 | 814 | 80,595 | $ 174 | 124 | 138 |
| Total | 712 | 9,434 | 779,738 | $ 145 | 104 | 952 |

**Historic Data for ASOM Baseline Markets**

**Historic Baseline** **(b)**

| | 3QTR 2007 Baseline Statistics | | | | | |
|---|---|---|---|---|---|---|
| | Geographic Access | | Economic Access | | ATS Efficiency | |
| | Markets | Flights | Demand | Avg Airfare | Avg Aircraft Size | Daily ASMs (M) |
| BOS | 64 | 865 | 69,640 | $152 | 101 | 84 |
| DFW | 121 | 1,660 | 149,449 | $133 | 112 | 162 |
| EWR | 74 | 898 | 73,365 | $166 | 102 | 103 |
| JFK | 48 | 782 | 72,554 | $166 | 116 | 116 |
| LGA | 64 | 990 | 69,438 | $134 | 95 | 65 |
| PHL | 134 | 2,244 | 180,461 | $136 | 98 | 194 |
| ORD | 80 | 1,146 | 83,084 | $126 | 96 | 88 |
| SFO | 53 | 793 | 80,273 | $175 | 127 | 138 |
| Total | 638 | 9,378 | 778,264 | $145 | 104 | 951 |

**ASOM Aggregate Schedule**

**ASOM – VFR at $2 fuel prices** **(c)**

| | 3QTR 2007 Baseline Statistics | | | | | |
|---|---|---|---|---|---|---|
| | Geographic Access | | Economic Access | | ATS Efficiency | |
| | Markets | Flights | Demand | Avg Airfare | Avg Aircraft Size | Daily ASMs (M) |
| BOS | 64 | 724 | 61,898 | $ 148 | 102 | 63 |
| DFW | 121 | 1,538 | 140,382 | $ 131 | 111 | 140 |
| EWR | 74 | 750 | 61,730 | $ 160 | 97 | 75 |
| JFK | 48 | 624 | 61,134 | $ 152 | 118 | 81 |
| LGA | 64 | 880 | 64,792 | $ 132 | 89 | 52 |
| PHL | 134 | 1,966 | 169,240 | $ 135 | 108 | 168 |
| ORD | 80 | 958 | 79,760 | $ 118 | 101 | 73 |
| SFO | 53 | 688 | 63,200 | $ 180 | 115 | 98 |
| Total | 638 | 8,128 | 702,136 | $ 141 | 105 | 750 |

**% difference from historic benchmark**

**ASOM/ Historic** **(d)**

| | 3QTR 2007 Baseline Statistics | | | | | |
|---|---|---|---|---|---|---|
| | Geographic Access | | Economic Access | | ATS Efficiency | |
| | Markets | Flights | Demand | Avg Airfare | Avg Aircraft Size | Daily ASMs (M) |
| BOS | 100% | 84% | 89% | 98% | 101% | 75% |
| DFW | 100% | 93% | 94% | 99% | 99% | 86% |
| EWR | 100% | 84% | 84% | 96% | 95% | 72% |
| JFK | 100% | 80% | 84% | 91% | 102% | 69% |
| LGA | 100% | 89% | 93% | 99% | 94% | 80% |
| PHL | 100% | 88% | 94% | 99% | 110% | 87% |
| ORD | 100% | 84% | 96% | 94% | 105% | 83% |
| SFO | 100% | 87% | 79% | 103% | 91% | 71% |
| Total | 100% | 87% | 90% | 97% | 101% | 79% |
| | | 80%-93% | 79%-96% | 91%-103% | 91%-110% | 78%-87% |

**Figure 29 Historic scheduled service versus ASOM aggregate airline schedules, for $2 fuel price at VFR+ capacity limits**

When aggregating the schedule to these profitable markets the ASOM was found to have between 80%-93% of the historic frequency of service to the profitable markets found in the ASOM analysis. The ASOM schedule served 79%-96% of the historic passenger demand for these markets, with the ASOM SFO schedule showing the worst performance of 79%. The average airfares set by the ASOM were 91%-103% of the historic average airfares for these airports. The average aircraft size per operation for the ASOM schedules were 91%-110% of the size of historical operations for these markets. And the ASOM scheduled available seat miles were between 78% and 87% of historically flown available seat miles for these markets.

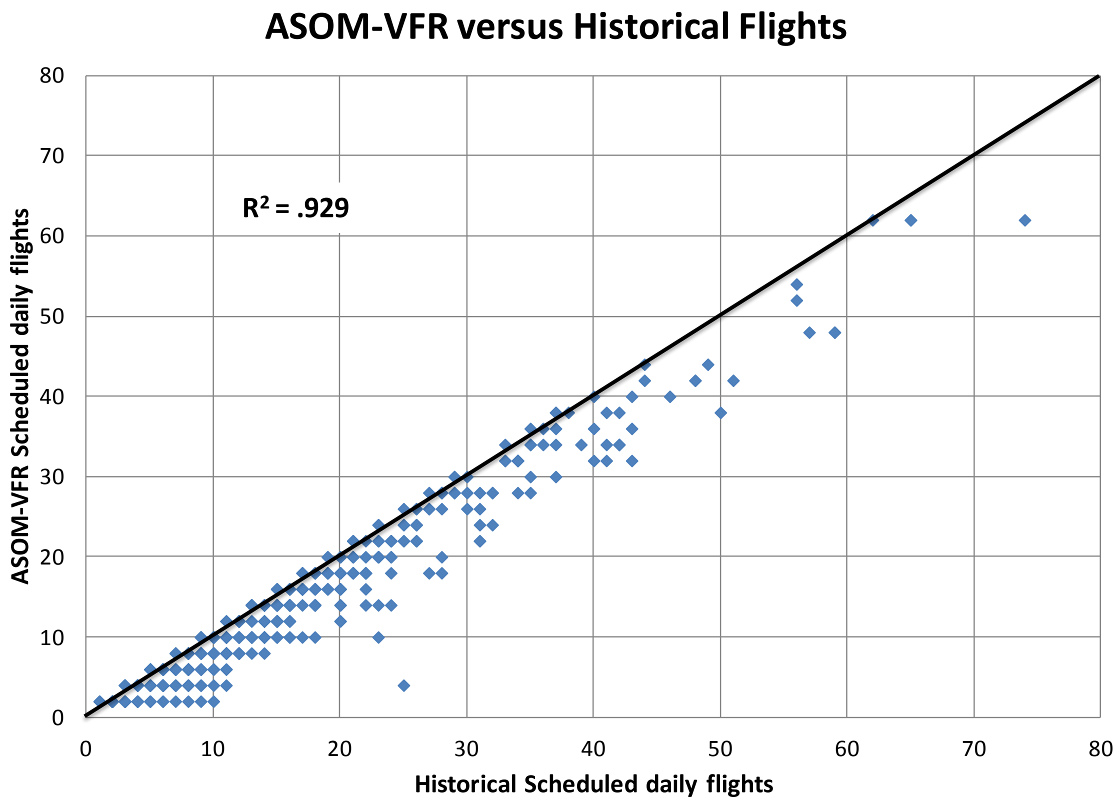



**Figure 30 Historic scheduled flights versus ASOM aggregate airline schedules, for $2 fuel price at VFR+ capacity limits**

An examination of 638 historically served and modeled as profitable markets by the ASOM at $2 fuel prices and VFR airport capacity levels is shown in Figure 30. While on the aggregate the ASOM schedules to these profitable markets were found to have between 80%-93% of the historic frequency, the model fit the historical data with a coefficient of determination ($R^2$) of 0.929. Since the ASOM models an aggregate airline versus competing airlines for each market, fewer flights are required to service the demand. The daily ASOM flights for markets never exceed the historic number of flights, since the ASOM is constrained to not increase the daily flights for a market.

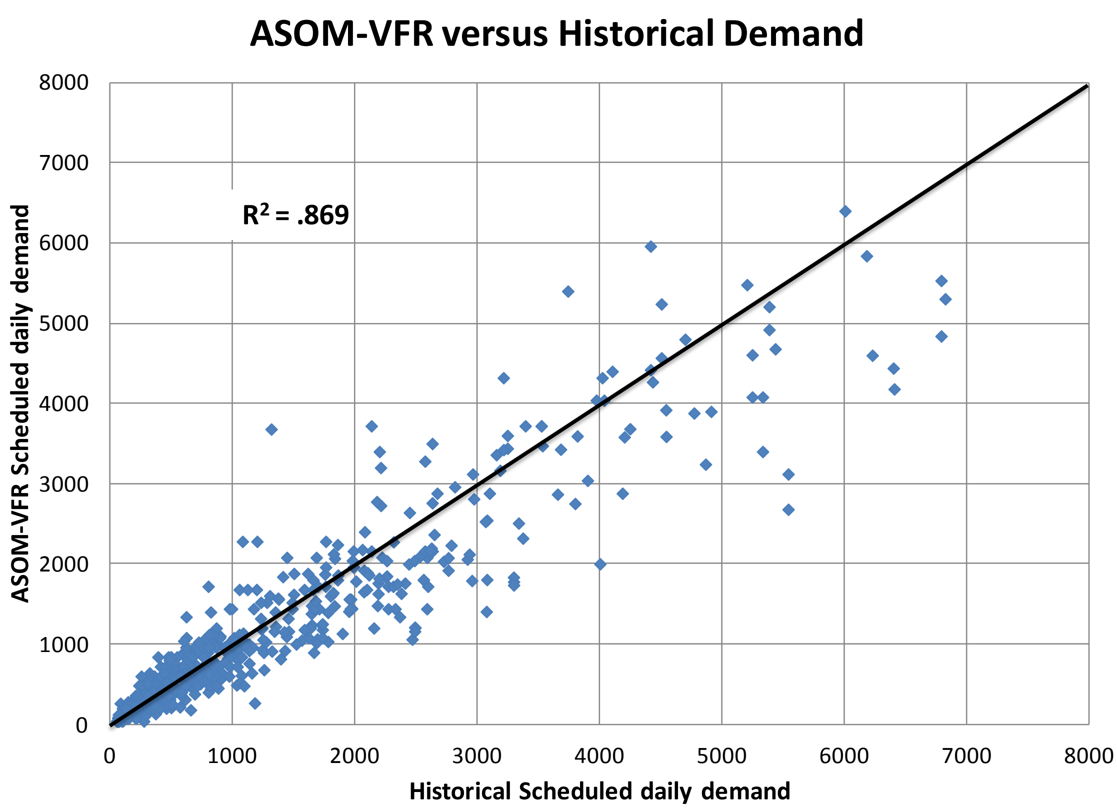



**Figure 31 Historic scheduled demand versus ASOM aggregate airline scheduled demand, for $2 fuel price at VFR+ capacity limits**

An examination of 638 historically served and modeled as profitable markets by the ASOM at $2 fuel prices and VFR airport capacity levels is shown in Figure 31. While on the aggregate the ASOM scheduled demand to these profitable markets were found to have between 79%-96% of the historic demand, the model fit the historical data with a coefficient of determination ($R^2$) of 0.869. The ASOM is allowed to up gauge or down gauge to the most profitable size aircraft to serve the demand for each market, so it is not surprising to see these results in Figure 31.

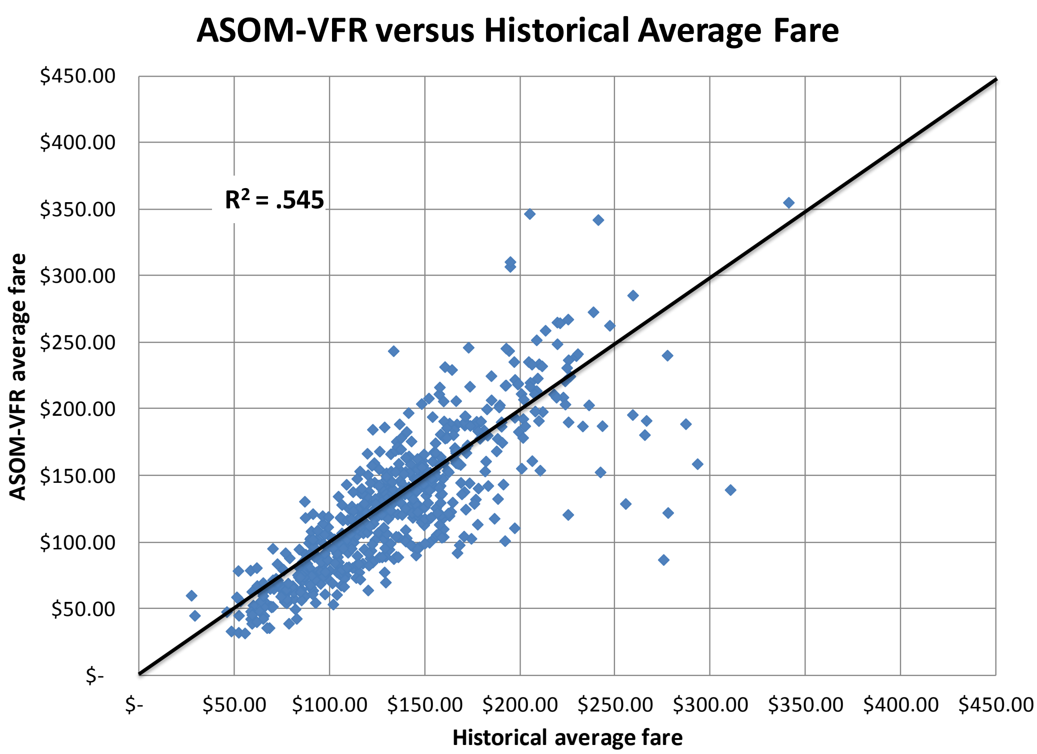



**Figure 32 Historic airfares versus ASOM aggregate airline scheduled airfares, for $2 fuel price at VFR+ capacity limits**

An examination of 638 historically served and modeled as profitable markets by the ASOM at $2 fuel prices and VFR airport capacity levels is shown in Figure 32. While on the aggregate the ASOM scheduled airfares for these profitable markets were found to be between 91%-103% of the historic airfares for these markets, the model fit the historical data with a coefficient of determination ($R^2$) of 0.545. The ASOM is allowed to up gauge or down gauge to the most profitable size aircraft to serve the demand for each market. Since the log-linear demand versus airfare curve is rather sensitive to changes in demand, it is not surprising to see these airfares vary so much from the historical airfares.

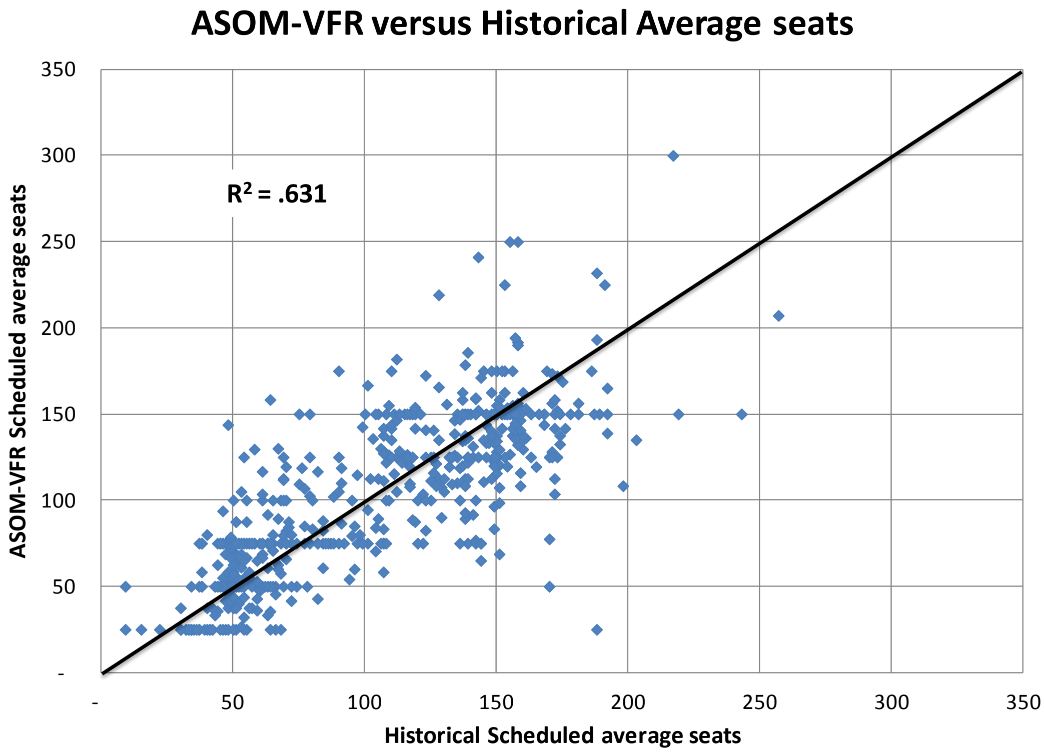



**Figure 33 Historic average aircraft sizes versus ASOM aggregate airline scheduled aircraft sizes, for $2 fuel price at VFR+ capacity limits**

An examination of 638 historically served and modeled as profitable markets by the ASOM at $2 fuel prices and VFR airport capacity levels is shown in Figure 33. While on the aggregate the ASOM scheduled aircraft sizes for these profitable markets were found to be between 91%-110% of the historic average aircraft sizes for these markets, the model fit the historical data with a coefficient of determination ($R^2$) of 0.631. These are expected results since the ASOM is allowed to up gauge or down gauge to the most profitable size aircraft to serve the demand for each market.

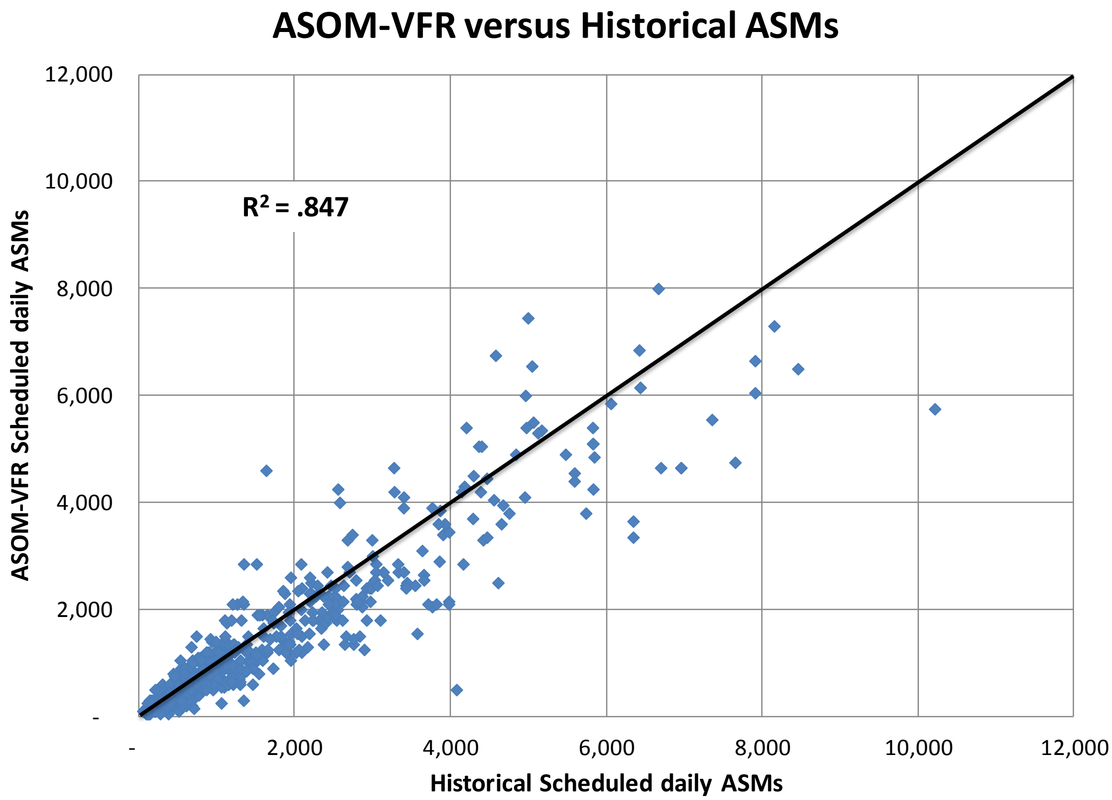



**Figure 34 Historic daily ASMs flown versus ASOM aggregate airline scheduled ASMs, for $2 fuel price at VFR+ capacity limits**

An examination of 638 historically served and modeled as profitable markets by the ASOM at $2 fuel prices and VFR airport capacity levels is shown in Figure 34. While on the aggregate the ASOM scheduled ASMs for these profitable markets were found to be between 78% and 87% of the historic average daily ASMs flown for these markets, the model fit the historical data with a coefficient of determination ($R^2$) of 0.847.

This analysis shows the aggregated schedules for the ASOM are very similar to the historically flown schedules, therefore this analysis provides confidence in the following analysis of airline scheduling and passenger demand behavior for the non-historically based scenarios described in the following sections.

## 4.6. Airport Schedule Optimization Model (ASOM) Conclusions

The ASOM is a valid and robust model to predict airline scheduling and pricing behavior in response to economic and runway capacity changes. The ASOM provides a capability for the airline industry to examine how the economics of passenger price elasticity, aircraft performance and cost affect the airlines profitability.

# Chapter 5 – Effects of Capacity Limits and Aviation Fuel Prices on Airline Schedules for Congested Airports

This experiment examines how airlines are likely to respond in terms of their domestic schedules and airfares to increases in fuel prices and reduced runway capacity limits. Passengers also respond to the airlines schedule and airfares by altering their demand. The ASOM model, being an equilibrium model, considers the interactions between price and passenger demand and establishes new schedules (both size of aircraft and frequency of flights to markets) that maintains airline profitability. This analysis provides insight on how operational costs (fuel prices) and policy (runway capacity limits) effect the availability of air transportation to individual markets and the likely delays in air transportation service that result from changes in airline schedules due to limitations in runway capacity..

This analysis shows reductions in runway capacity limits (-8 ops/hr) results in only slight changes in markets served (-1%), the frequency of service (-2%), the passengers served (-1%), the airfares (+0.4%), the average seat per flight (+1%), the daily fuel burn (-1%), and the available seat miles (-1%) flown in the schedule.  Thus while small reductions in the runway capacity at congested airports reduces congestion, it does not significantly reduce the service to the domestic markets. These findings from this analysis were consistent with historical analysis of the few congested airports where capacity was reduced from 2005 to 2009. (Ferguson et al. 2010)

This analysis shows increases in fuel prices (+$1/gal) results in relatively minor changes in markets served (-1%), the frequency of service (-1%), and the airline profits (-3%). However, increases in fuel prices (+$1/gal) resulted in significant reductions in the passengers served (-9%), the average seats per flight (-8%), the daily fuel burn (-8%), and the available seat miles (-9%) flown in the schedule. And increases in fuel prices (+$1/gal) resulted in significant increases in the average airfare (+19%). Thus, fuel prices (or any significant increase in airline operational costs) are shown have significant effect on airline schedules and airfares. These findings from this analysis were consistent with historical analysis of airports during the period of 2005 to 2009 where fuel prices ranged between $1.33 and $3.50. (Ferguson et al. 2010)

In the following sections the design of experiment, the methodology, the results from the experiment and a summary of the findings will be presented.

## 5.1. Design of Experiment

This analysis compares the Airport Schedule Optimization Model (ASOM) schedules and airfare outputs for eleven non-historical scenarios for fuel price and runway capacity to a baseline analysis of third quarter 2007 when fuel prices were $2 per gallon. The baseline used VFR capacity limits at all airports.

This chapter shows the results from an experiment on eight congested airports during the most congested quarter in recent history, 3rd quarter 2007. This experiment shows the effects of airport capacity limits and increased fuel prices on markets served, frequency of service, available seat miles, passengers served, average airfares for this service, daily airline profits and daily fuel burn at these eight congested airports (BOS, DFW, EWR, JFK, LGA, ORD, PHL, and SFO). These airports generated 47.5% of the flight delays in 2007 and 42.6% of the flight delays in 2010 for domestic air transportation in the NAS. This analysis evaluates these metrics across non-historical scenarios as compared to the base historical scenario (3rd quarter 2007).

The Airport Schedule Optimization Model (ASOM) was used to model airline scheduling behavior and passenger demand behavior in response to adjusted airport runway capacity limits and increased fuel prices. The design of experiment used to answer these research questions introduced at the beginning of this chapter is shown in Table 24. 96 different scenarios or airport schedules are examined in this experiment.

## Table 24 Design of experiment

| INPUTS | | | OUTPUTS | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Supply/ Costs | | | | Demand/ Revenue | | Equilibrium Results | |
| Airport | Runway Capacity | Fuel Price | Markets Served | Flights/ Day | Seats/ Flight | ASMs | Passenger Demand | Average Airfare | Airline Profits | Fuel Burn |
| Boston | VFR | $2 | | | | | | | | |
| | | $3 | | | | | | | | |
| | | $4 | | | | | | | | |
| | | $5 | | | | | | | | |
| | MVFR | $2 | | | | | | | | |
| | | $3 | | | | | | | | |
| | | $4 | | | | | | | | |
| | | $5 | | | | | | | | |
| | IFR | $2 | | | | | | | | |
| | | $3 | | | | | | | | |
| | | $4 | | | | | | | | |
| | | $5 | | | | | | | | |
| DFW | | | | | | | | | | |
| EWR | | | | | | | | | | |
| JFK | | | | | | | | | | |
| LGA | | | | | | | | | | |
| ORD | | | | | | | | | | |
| PHL | | | | | | | | | | |
| SFO | | | | | | | | | | |

**Current Fleet Options
8 airports X 4 Fuel Prices X
3 Capacity Limits =
96 Runs/ Schedules**

The eight airports examined in this study provide a nice cross section of domestic and international hubs, competitive and non-competitive airports, and a few airports which predominately serve non-stop domestic markets, see Table 25. (U.S. DOT/BTS 2010)

**Table 25  Cross-sectional analysis of congested airports**

| | Hub | | | | non-stop |
|---|---|---|---|---|---|
| | domestic | | international | | domestic |
| | single airline | competitive | single airline | competitive | competitive |
| BOS | | | | | x |
| DFW | x | | | | |
| EWR | | | x | | |
| JFK | | | | x | |
| LGA | | | | | x |
| ORD | | x | | | |
| PHL | | x | | | |
| SFO | | | x | | |

To examine the effects of runway capacity limits on airline scheduling and passenger demand behavior, the capacity limits for hourly airport operations were set based upon the FAA study to benchmark airline levels of operation for three different capacity levels:  (1) visual flying rules (VFR), (2) marginal visual flying rules (MVFR), and (3) instrument flying rules (IFR). (Barkeley 2004)  These different runway capacity levels for the eight airports are shown in Table 26 below.  Table 26 also illustrates the average hourly historical arrival and departure operations from 6am to 10pm for third quarter 2007.  Looking at this table one sees that ORD historic operations were significantly greater than VFR capacity and SFO historic operations were significantly less than the lowest capacity levels considered.  The other six airports historic operations were at or above the MVFR capacity levels.

**Table 26 Operations per hour modeled versus historical average hourly operation rates; source (Barkeley 2004) (U.S. DOT/BTS 2010)**

| Capacity Limits (Ops per hour) Model Inputs | | | Actual avg ops/hr 3QTR 2007 b/w 6am-10pm |
|---|---|---|---|
| VFR+ | MVFR | IFR | |
| 88 | 64 | 48 | 75 |
| 168 | 136 | 104 | 134 |
| 88 | 80 | 64 | 79 |
| 88 | 80 | 64 | 81 |
| 88 | 80 | 72 | 77 |
| 160 | 144 | 128 | 180 |
| 96 | 80 | 72 | 87 |
| 96 | 80 | 72 | 65 |

To examine the effects of aviation fuel prices on airline scheduling and passenger demand behavior, the fuel prices were set for $2, $3, $4 and $5. While, historic aviation fuel prices have only reached $3.50 – once in 3rd quarter 2008 – as in Figure 35 below, this experiment will examine the effects of aviation fuel prices up to $5.

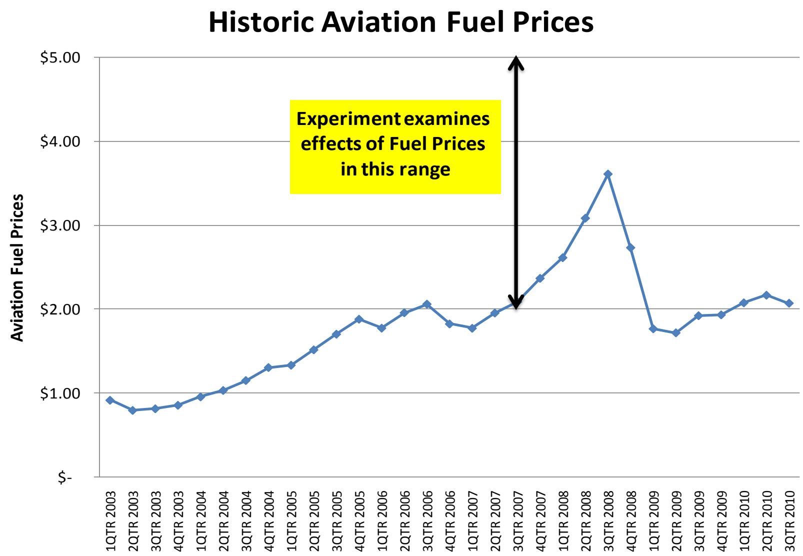



**Figure 35  Historic aviation fuel prices from 2003 to 2010; source (U.S. DOT/BTS 2010)**

## 5.2. The Airport Schedule Optimization Model (ASOM)

The ASOM is a multi-commodity model that optimizes the schedule of aircraft serving an airport while satisfying market demand. The ASOM, based on an earlier model (L. T. Le 2006) selects an optimal schedule for an airport by selecting profitable markets. We define a profitable market as a market served by the airport that had positive profit when summing all operations during summer 2007. Each such markets compete for the available arrival and departure capacity of the studied airport against all other profitable markets. The model also incorporates demand elasticity curves based on historical data that provide information about how passenger demand is impacted by airfare changes.

### 5.2.1. Assumptions for the ASOM

The ASOM models the airline industry as a single airline that is an aggregate model of the activities of the entire airline industry. This single airline provides service to all of the markets currently served.

The model selects only aircraft classes (increments of 25 seats) for each market's schedule based on aircraft historically flown to each market. For example, if 100 seat class aircraft (between 87 and 112 seat) have not historically been flown[1] for a specific market, the ASOM will not be able to select this aircraft for the optimal airport schedule.

The model will determine aircraft size based on an expectant load factor of 80% or better. Since 2007, load factors have risen to almost 90% (2010, BTS data). If demand is insufficient to fill 80% of a plane, then the model will choose a smaller aircraft to fly.

Historic aircraft non-fuel costs and burn rates remain constant for all scenarios examined. And the proportion of passenger demand by time of day for a market remains unchanged across all scenarios.

[1] Historically flown means that some airline flew that aircraft type sometime between 2005 and 2009.

### 5.2.2. Inputs for the ASOM

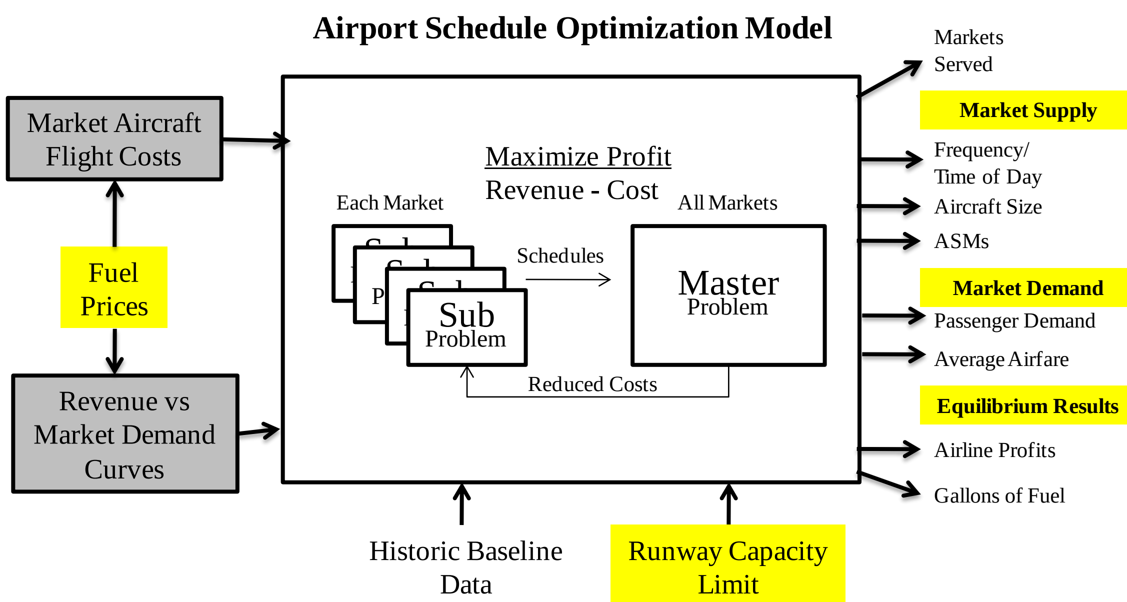



**Figure 36 The airport schedule optimization model (ASOM)**

The ASOM model is summarized in Figure 36. The inputs to the model are as follows:

(1) Airport capacity limits for domestic operations: The number of scheduled international flights and cargo flight are subtracted from the target airport capacity to obtain the airport capacity for domestic operations. These capacity limits are adjusted to represent visual flight rules (VFR), marginal VFR (MVFR), and instrument flight rules (IFR) conditions.

(2) Airline hedged fuel prices: The baseline price of $2 per gallon observed in 3QTR 2007 was used. This price was varied upward in $1 increments to $5 in order to see how large shocks to operational prices would impact schedules and airfares.

(3) Market operational flight costs by aircraft type: The total operational cost of a flight is altered based on the aircraft type used. The ASOM allows all aircraft to be considered for specific markets, whether it was used historically or not. Fuel costs are based on the burn rates of the aircraft type. Crew costs are specific to the aircraft type. All other costs are based on average costs for the industry. These costs include ticketing, gating, baggage, maintenance, depreciation, and a variety of other incidental costs.

(4) Market demand versus airfare: Demand curves are derived by taking the summer 2007 data that reflects the percentage of tickets bought at each of the airfare classes for each market served. For ASOM runs where only the capacity is varied, these curves do not change. For runs where fuel prices are changed, the curves are adjusted for changes in airline fuel prices as shown in Table 27 below. For example when changing the airline fuel prices from the historic position of $2 for 3$^{rd}$ quarter 2007 to $3, all market intercepts are reduced by -0.52% and their respective price coefficients are also reduced by -12.59%. Further discussion of the development of these relationships between fuel price and passenger demand versus airfare curves is discussed in chapter 3 of this dissertation.

**Table 27 ASOM adjustments for economic changes for the market passenger demand versus airfare curves**

**Changes for individual market curves due to Economy**

| | $1 increase in Fuel Price | 1% increase in unemployment |
|---|---|---|
| Demand Coef Change (intercept) | -0.52% | -0.33% |
| Price Coef Change (slope) | -12.59% | -1.80% |

### 5.2.3. Outputs for the ASOM

The outputs of the ASOM are a profitable, feasible schedule to each profitable market scheduled. The schedule indicates the time of each flight in the schedule and the aircraft type used. The following metrics can be determined from this schedule:

(5) Number of markets served

(6) Number of daily flights to each market

(3) Aircraft size chosen for each flight

(4) Available seat miles

(5) Passenger demand served in schedule

(6) Average passenger airfare

(7) Total daily profit for each market served

(8) Total daily fuel used from the scheduled flights

### 5.2.4. Economic Equilibrium

An equilibrium model is used to determine the most profitable schedule. First a collection of feasible schedules is generated for each market and based on these schedules a “master problem” is solved that chooses among these schedules an overall schedule for the airport. This master problem provides a measure of the value of an additional flight within any time period (shadow price information). This shadow price information (often referred to as a “dual price”) is used to calculate new schedules for each market. Thus, for each market, new schedules were collected based on these shadow prices. All such schedules are added to the master problem.

The master-problem again determines an optimal airport schedule by selecting market schedules that maximizes profit for the airport within the operational capacity of the airport. The process iterates between the solution of the master problem and the generation of new market schedules until no new schedules exist that can improve the master problem. This overall approach is called “Column Generation.”

Once the problem is solved to linear optimality, if the solution obtained is not integer, a tree search is invoked to prove integer optimality using the same column-generation approach on each branch of the tree.

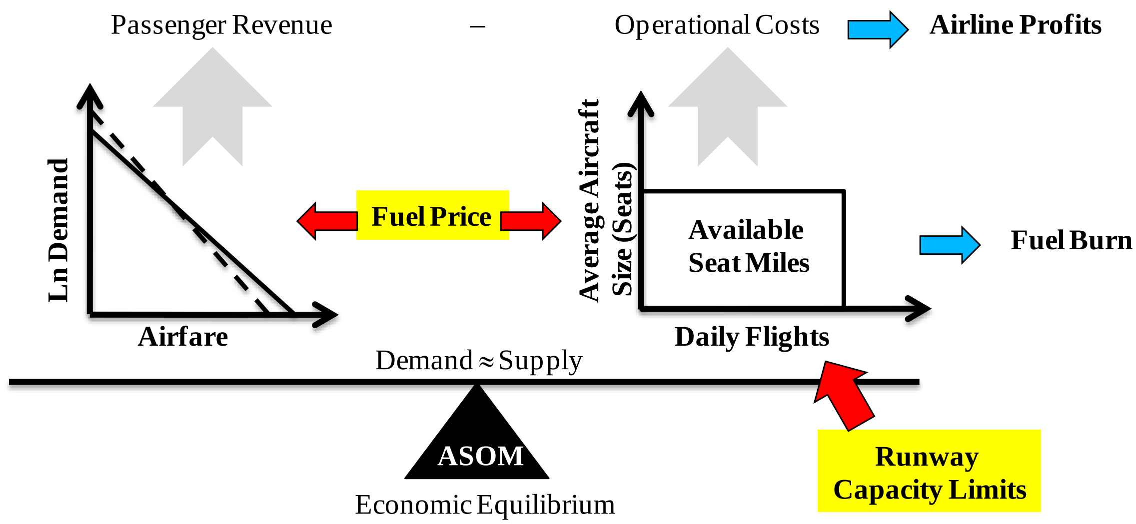



**Figure 37 Market equilibrium between operational costs and passenger revenue in the ASOM**

Figure 37 also illustrates basic economic relationships. For example, the model will choose an aircraft type so that the profit from that flight is maximized and the demand for the flight is approximately equal to the seat size of the aircraft. The model must assess if it is better to accept a lower average price per seat but greater demand or a higher price with lower demand. Fuel burn impacts this decision since larger aircraft have higher burn rates and these costs are part of the profit calculation.

The ASOM is discussed in greater detail in chapter 4 of this dissertation.

### 5.2.5. Data sources for the ASOM

The BTS (U.S. DOT/BTS 2010) and ASPM (FAA 2007) data was preprocessed for the eight airports for third quarter 2007 to calculate the inputs for the ASOM. The following databases were specifically used to preprocess the ASOM data; the ASPM Individual Daily Flight, the T100 monthly flight summaries, the DB1B quarterly passenger itineraries, the P52 quarterly airline costs and the CATSR airport and aircraft data databases. Full descriptions of these databases and how they are used within the ASOM model are provided in Chapter 4.

## 5.3. Results

The impacts of fuel price increases and runway capacity limits on these aggregate domestic airline schedules are examined through changes in markets served, frequency of service, available seat miles, passengers served, average airfares for this service, daily airline profits and daily fuel burn. The results of this analysis show:

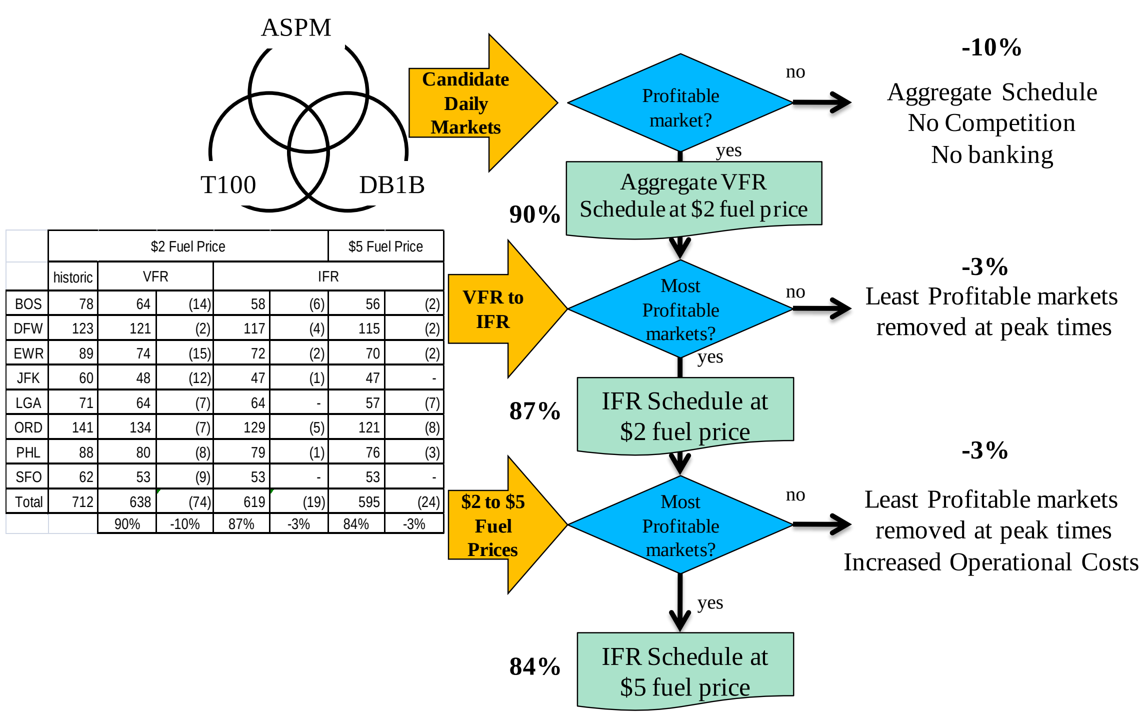
i. Airlines can maintain profitable and affordable service for domestic markets when runway capacity limits are reduced.

ii. Increases in fuel prices (+$1/gallon) results in significant down gauging (-8%), reduced service to smaller markets (-9% ASMs) and increased airfares (+19%).

iii. Increases in fuel price (+$1/gallon) reduce passenger price elasticity (-13%).

### 5.3.1. Markets dropped due to profitability, capacity, or increased fuel prices

Figure 38 shows that 74 (-10%) of the 712 historic daily markets for the eight airports examined are not included in the aggregate airline schedules for the baseline case: VFR capacity limits and $2 fuel prices. The data provided to the model indicated that in 2007 these markets were not, on average, profitable during the summer 2007. An airline may choose to remain in the market for strategic reasons (e.g. maintain market share), regulatory reasons (e.g. airline received slots at a controlled airport with a promise to serve under-served markets), or because additional congestion or maintenance problems forced unforeseen costs. These markets cannot be examined in this experiment since they are not included in the baseline scenario schedules.




| | $2 Fuel Price | | | | | $5 Fuel Price | |
|---|---|---|---|---|---|---|---|
| | historic | VFR | | IFR | | | |
| BOS | 78 | 64 | (14) | 58 | (6) | 56 | (2) |
| DFW | 123 | 121 | (2) | 117 | (4) | 115 | (2) |
| EWR | 89 | 74 | (15) | 72 | (2) | 70 | (2) |
| JFK | 60 | 48 | (12) | 47 | (1) | 47 | - |
| LGA | 71 | 64 | (7) | 64 | - | 57 | (7) |
| ORD | 141 | 134 | (7) | 129 | (5) | 121 | (8) |
| PHL | 88 | 80 | (8) | 79 | (1) | 76 | (3) |
| SFO | 62 | 53 | (9) | 53 | - | 53 | - |
| Total | 712 | 638 | (74) | 619 | (19) | 595 | (24) |
| | | 90% | -10% | 87% | -3% | 84% | -3% |

**Figure 38 Analysis of markets lost in the ASOM schedule due to profitability, capacity, or increased fuel prices**

When airport capacity rates are lowered from VFR to IFR rates, 19 of the remaining 638 (-3%) markets are not included in the schedule. The reduction in capacity resulted in the least profitable markets being removed from the schedule.

When aviation fuel prices are raised from $2 to $5, 24 of the remaining 619 (-3%) markets are not included in the schedule. This is caused by the inability of the airlines to pass enough of the increased operating costs on to the passengers to remain profitable. Based upon the individual passenger demand versus airfare curves, flights become unprofitable as fuel prices increase.

**Table 28 Flights removed from schedule due to profitability, capacity, or increased fuel prices**

| | | Flights | | | | |
|---|---|---|---|---|---|---|
| | | lost Markets | | | same Markets | |
| | historic daily Flights | not profitable | VFR to IFR | $2 to $5 | VFR to IFR | $2 to $5 |
| BOS | 887 | 58 | 16 | 22 | 124 | 22 |
| DFW | 1,675 | 3 | 16 | 12 | 158 | 74 |
| EWR | 901 | 33 | 4 | 6 | 99 | 30 |
| JFK | 785 | 50 | 2 | - | 84 | 38 |
| LGA | 1,001 | 22 | - | 38 | - | 60 |
| PHL | 2,267 | 16 | 24 | 14 | 262 | 48 |
| ORD | 1,161 | 34 | 4 | 18 | 106 | 26 |
| SFO | 814 | 34 | - | - | 4 | 34 |
| Total | 9,491 | 250 | 66 | 110 | 837 | 332 |
| | 100% | 3% | 1% | 1% | 9% | 3% |

Table 28 shows, for each airport studied the number of markets that were removed from the schedule due to loss of profitability or capacity reductions. This data indicates that although a number of markets were removed, these markets made up only 3% of the flights. Similarly, of those markets that remained, another 14% of the flights were removed during the most extreme conditions: IFR and $5.00 fuel prices.

**Table 29 Passenger Demand not served in schedule due to profitability, capacity, or increased fuel prices**

| | Demand | | | | | |
|---|---|---|---|---|---|---|
| | | lost Markets | | | same Markets | |
| | historic daily Demand | not profitable | VFR to IFR | $2 to $5 | VFR to IFR | $2 to $5 |
| BOS | 69,855 | 767 | 454 | 770 | 4,940 | 18,380 |
| DFW | 149,766 | 144 | 400 | 728 | 5,560 | 37,736 |
| EWR | 73,710 | 1,818 | 200 | 168 | 3,883 | 16,138 |
| JFK | 72,998 | 2,388 | 240 | - | 7,016 | 15,462 |
| LGA | 69,568 | 278 | - | 1,280 | - | 14,418 |
| PHL | 181,372 | 1,917 | 960 | 720 | 8,800 | 48,760 |
| ORD | 83,473 | 748 | 160 | 1,244 | 3,718 | 21,562 |
| SFO | 80,595 | 1,400 | - | - | 80 | 18,240 |
| Total | 781,337 | 9,460 | 2,414 | 4,910 | 33,997 | 190,696 |
| | 100% | 1% | 0% | 1% | 4% | 24% |

Table 29 shows that the 16% loss of markets, due to profitability, capacity, or increased fuel prices, reduce the passengers served by only 2%. Further examination shows that only 4% of the reduction of passengers served in the schedule due to changes in runway capacity limits or increased fuel prices can be attributed to lost markets.

**Table 30 % Changes (VFR $2 versus IFR $5) in metrics from dropped and kept markets**

| | Flights | Passenger Demand | Avg Airfare | Daily Profits | Fuel Burn | Aircraft Size | Daily ASMs |
|---|---|---|---|---|---|---|---|
| Impact from dropped Markets (43) | -2% | -1% | 0% | 0% | -1% | -1% | -1% |
| Impact from changes in kept Markets (595) | -12% | -30% | 60% | -12% | -29% | -19% | -29% |

Table 30 illustrates the overall impact on metrics examined in this study from the 43 markets dropped from the schedule due to reduced capacity or increased fuel prices versus from the 595 markets kept in the study for all scenarios examined. It is clear from this analysis that even though the percentage of markets dropped is large the impact is relatively small compared to the markets that remain in the schedule.

To better understand the impacts of capacity limits and fuel price increases on airline scheduling and passenger demand behavior, this analysis examines the 595 markets which are present in all scenarios.

### 5.3.2. Trend analysis

To better understand the impacts of capacity limits and fuel price increases on airline scheduling and passenger demand behavior, this analysis examines the 595 markets which are present in all scenarios. This analysis found that the effects of fuel price increases on airline scheduling and pricing behavior dominated the effects of reduced runway capacities. When capacity limits are reduced smaller aircraft serving less profitable markets are removed from the schedule first. As fuel prices increase flights flown with 150 seat aircraft are replace with 25 seat and 75 seat aircraft with higher airfares to remain profitable for the airlines.

#### *5.3.2.1. Impact of reduced runway capacities on airline behavior*

These markets are examined to evaluate effects from reducing runway capacity limits from VFR and MVFR operational levels, with fuel prices fixed at $2 per gallon. Due to the peaked nature of most airport operations, reductions of capacities from VFR have much less effect compared to reductions of capacities from MVFR as shown in Figure 39.

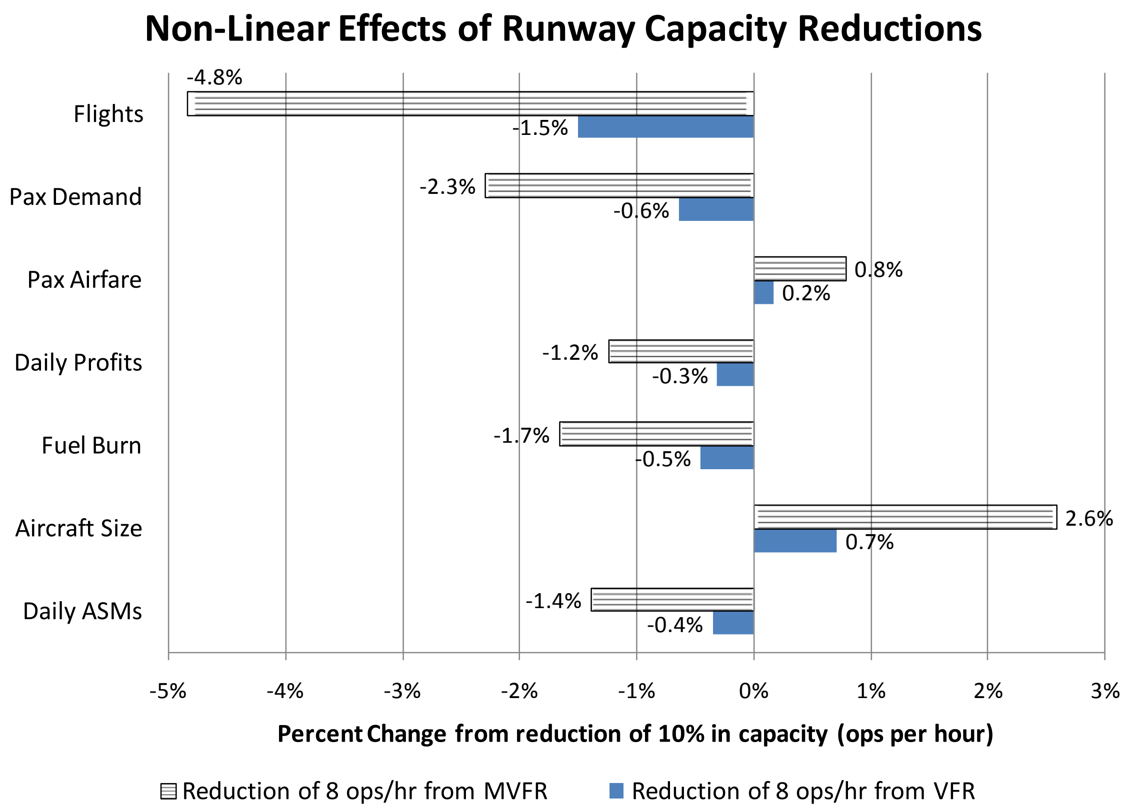



**Figure 39 Non-linear effects from runway capacity reductions**

On average all eight airports capacity are reduced -7% from a reduction of 8 operations per hour at VFR capacity levels and -9% from a reduction of 8 operations per hour at MVFR capacity levels. Figure 39 shows that this reduction of 9% in capacity at MVFR capacity levels affects three metrics more than 1.5%: flights are reduced 4.8%, passenger demand is reduced 2.3%, and aircraft size is increased 2.6%.

#### *5.3.2.2. Impact of increased fuel prices on airline behavior*

These markets are examined to evaluate effects from reducing runway capacity limits from $2 to $3, $3, to $4, and $4 to $5, with airport capacity limits fixed at VFR runway capacities. Increases in aviation fuel prices from $2 to $3 have more effect compared to increases in aviation fuel prices from $4 to $5, as shown in Figure 40.

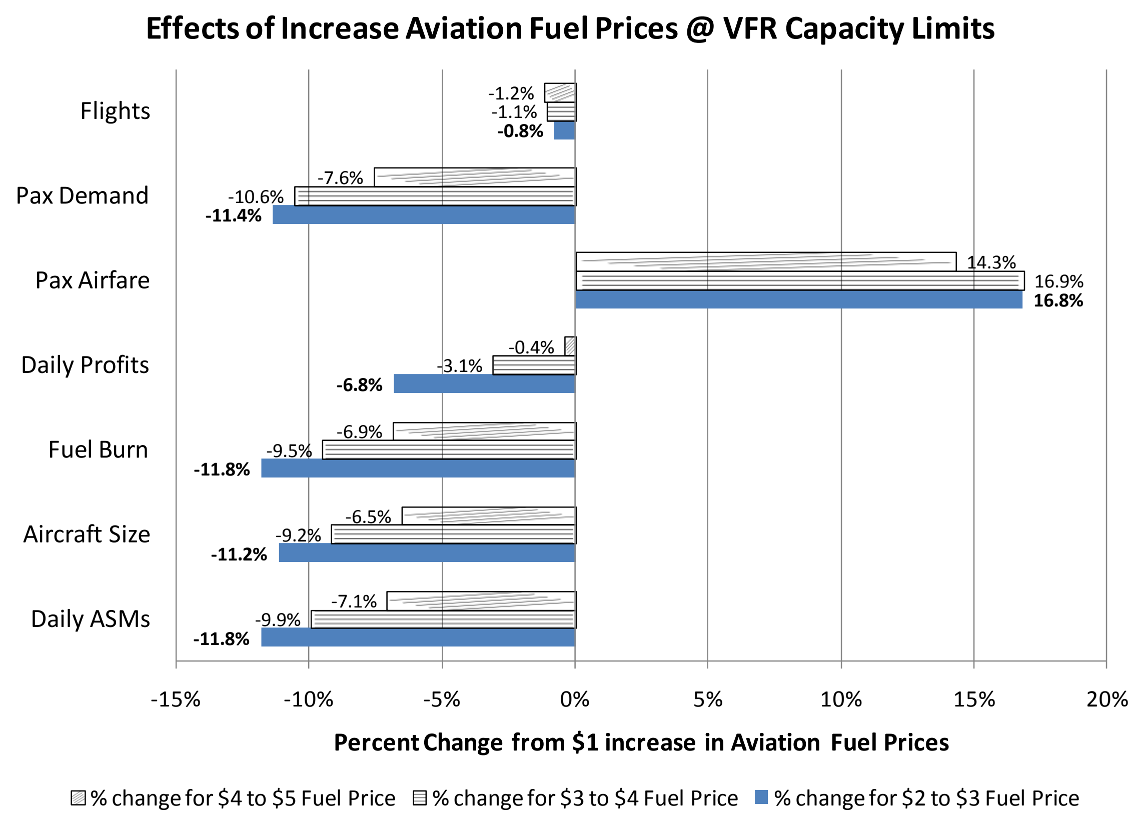



**Figure 40 Effects from increases in aviation fuel prices**

Increasing the aviation fuel prices from $2 to $3 in the ASOM triggers significant changes in almost all of the metrics examined. Frequency of service to markets is reduced by

1%, which is minor for a fuel price increase 50%. However, there are major changes in passenger demand (-11.4%), average airfare (+16.8%), daily airline profits (-6.8%), daily fuel burn (-11.8%), average aircraft size (-11.2%), and daily available seat miles (-11.8%). This loss of demand would likely have very negative impacts on the leisure travel industry. Even with the increased airfares, this analysis shows the airlines will struggle to maintain profits. Since the airlines cannot pass along all of the increases in operational costs on to the passenger, the overall profitability of the airline industry decreases. We also notice a significant shift to smaller aircraft since these are the newest portion of the industry's fleet and have better burn rates than larger aircraft. For more on this issue, see Section 4.2.2 of chapter 4 of this dissertation.

**Table 31 Percent change in scheduled flights for VFR runway capacity limits when fuel prices are increased from \$2/ gallon to \$5/ gallon, examined by aircraft size and airport.**

| | % Change in scheduled flights when fuel prices increased from \$2 per gallon to \$5 per gallon | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Aircraft size (seats per operation)** | **BOS** | **DFW** | **EWR** | **JFK** | **LGA** | **ORD** | **PHL** | **SFO** |
| **25** | **12%** | 3% | **19%** | 4% | **5%** | **12%** | **8%** | **9%** |
| **50** | 1% | | **-6%** | 1% | 1% | 1% | -1% | -1% |
| **75** | **17%** | **23%** | **5%** | **14%** | **8%** | **17%** | **21%** | 4% |
| **100** | | | -2% | 2% | | | | 1% |
| **125** | -3% | 1% | **11%** | -4% | **-6%** | -2% | 4% | **9%** |
| **150** | **-19%** | **-24%** | **-23%** | **-19%** | -3% | **-19%** | **-28%** | **-18%** |
| **175** | **-5%** | -2% | -4% | **-5%** | **-8%** | -2% | **-6%** | -1% |
| **200** | Not modeled in the ASOM due to lack of data in BTS for aircraft in this class | | | | | | | |
| **225** | | | | -1% | | -1% | -1% | |
| **250** | -2% | -3% | | | -1% | -4% | | **-8%** |
| **275** | | -1% | | | | -1% | | |
| **300** | | | | | | -1% | | -1% |

Next the effects of fuel price increase from $2 to $5 for all eight airports by aircraft size are examined in Table 31. This analysis shows most airport schedules reduce the use of flights from 150 seat aircraft and increase the use of 75 seat and 25 seat aircraft in the schedules at $5 fuel prices. The VFR schedule for LGA removes 125 seat and 175 seat aircraft from the schedule and increases the use of 75 seat and 25 seat aircraft. The VFR schedule for SFO removes 150 seat and 250 seat aircraft from the schedule and increases the use of 75 seat, 25 seat, and 125 seat aircraft.

### 5.3.3. Airport Schedule Optimization Model (ASOM) Statistical Analysis of Outputs

The following outputs of the ASOM were analyzed: (1) the number of profitable markets served, (2) the daily domestic flights by market, (3) the average revenue per seat, (4) the average aircraft size in seats per operation, and (5) the overall profitability of each airport studied. The controls or exogenous factors for the model are fuel prices and airport capacity limits.

The analysis of statistically significant trends between the exogenous factors and the ASOM outputs required the following multi-step process:

(1) The ASOM output data was processed into the metrics of interest at the airport level.

(2) A step-wise regression was performed to identify the factors that most impact the independent variable. Stepwise regression adds variables sequentially, choosing the most significant variable first and continues until the adding of another variable degrades the relative R2 coefficient (i.e. the R2 adjusted for the number of independent terms in the regression equation).

A regression analysis was performed on the ASOM output metrics model the average effects of runway capacity limits and increased fuel prices on flight frequency, passenger demand, average airfare, airline profitability, fuel burn, average aircraft size or seats per operation and available seat miles in the schedule. We use the data from the 96 different scenarios (8 airports x 3 capacity limits x 4 fuel prices) for this analysis. These metrics were normalized for each airport by dividing the value by its corresponding airport value for VFR capacities and $2 fuel prices. This normalization allows one to compare airports with fewer flights to those with larger flights. The measures were calculated for the 595 markets that remain in the airport schedules. Airport dummy variables were included in the model to see if any airport responded differently from the others. We used the following regression model:

(Flights in schedule for scenario with capacity '*A*' and with fuel prices '*B*')/ (flights in schedule for scenario with VFR capacity and with fuel prices $2) =

$$Constant + Coef_{capacity} * A + Coef_{fuel\ price} * B + Coef_{BOS} + Coef_{DFW} + Coef_{EWR} + Coef_{JFK} + Coef_{LGA} + Coef_{ORD} + Coef_{PHL} + Coef_{SFO}$$

The results of this analysis produced models for the metrics that fit the original data values with adjusted $R^2$ values ranging between 64% and 99% as shown in Table 32. When a coefficient listed in Table 32 was found not to statistically improve the model, based upon the t-test at a 90% level of confidence, then the entry if left blank in the table. The coefficient for capacity was found to statistically improve all but one model, capacity was found not to statistically improve the model for airline profit. The coefficient for fuel price was found to statistically improve all models examined.

**Table 32 Regression Coefficients for Regression model of ASOM outputs**

| | flights | demand | ASMs | Profit | Fuel Burn | avg Airfare | seats/flight |
|---|---|---|---|---|---|---|---|
| Constant | 74% | 105% | 108% | 105% | 106% | 68% | 128% |
| **Coefficients** | | | | | | | |
| **Capacity (8 ops/hr)** | **2%** | **1%** | **1%** | | **1%** | **-0.4%** | **-1%** |
| **Fuel Price ($1/gal)** | **-1%** | **-9%** | **-9%** | **-3%** | **-8%** | **19%** | **-8%** |
| BOS | 6% | | | 2% | | | -3% |
| DFW | -12% | -7% | -3% | | -6% | 2% | 7% |
| EWR | 2% | | 1% | | | | |
| JFK | | -2% | | -7% | | -3% | |
| LGA | 6% | 4% | 4% | 5% | 3% | -5% | |
| ORD | -16% | -9% | -6% | | -9% | 3% | 7% |
| PHL | | -2% | | | -2% | | |
| SFO | 4% | | | -3% | | -2% | -2% |
| | | | | | | | |
| **adj R2** | **64%** | **94%** | **94%** | **73%** | **94%** | **99%** | **93%** |

These models derived from the ASOM schedules, fitted with coefficients for the eight airports, provides a good representation of the response of airline scheduling and passenger demand behavior in response to runway capacity limit changes and fuel price changes.

A comparison of the separate analyses of capacity and fuel price effects on the metrics of interest are made to the coefficients found in regression models for each of the corresponding metrics, see Figure 41.

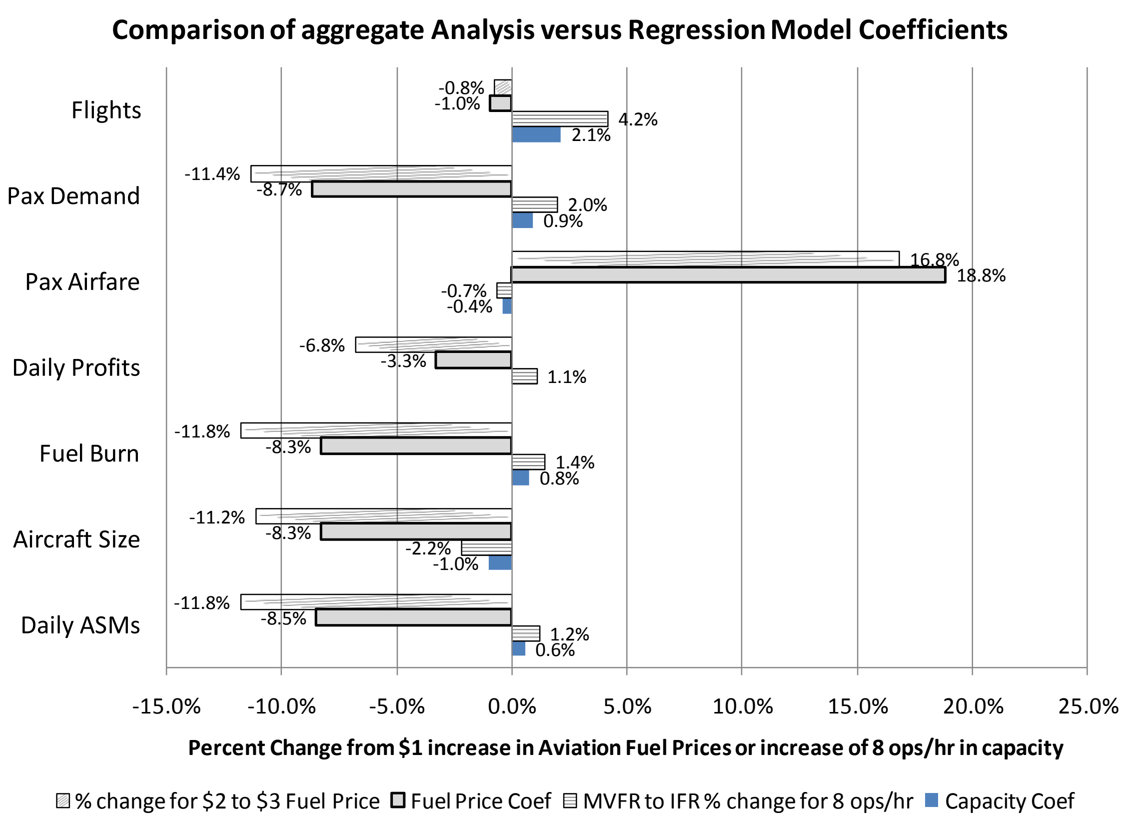


**Figure 41 Comparison of separate analysis of capacity and fuel price effects on metrics compared to regression model coefficients**

The following sections describe the models found through the regression analysis and provides goodness of fit analysis of these models.

### *5.3.3.1. Model of Flights per day as a percentage of Flights per day in VFR schedules at $2 fuel prices*

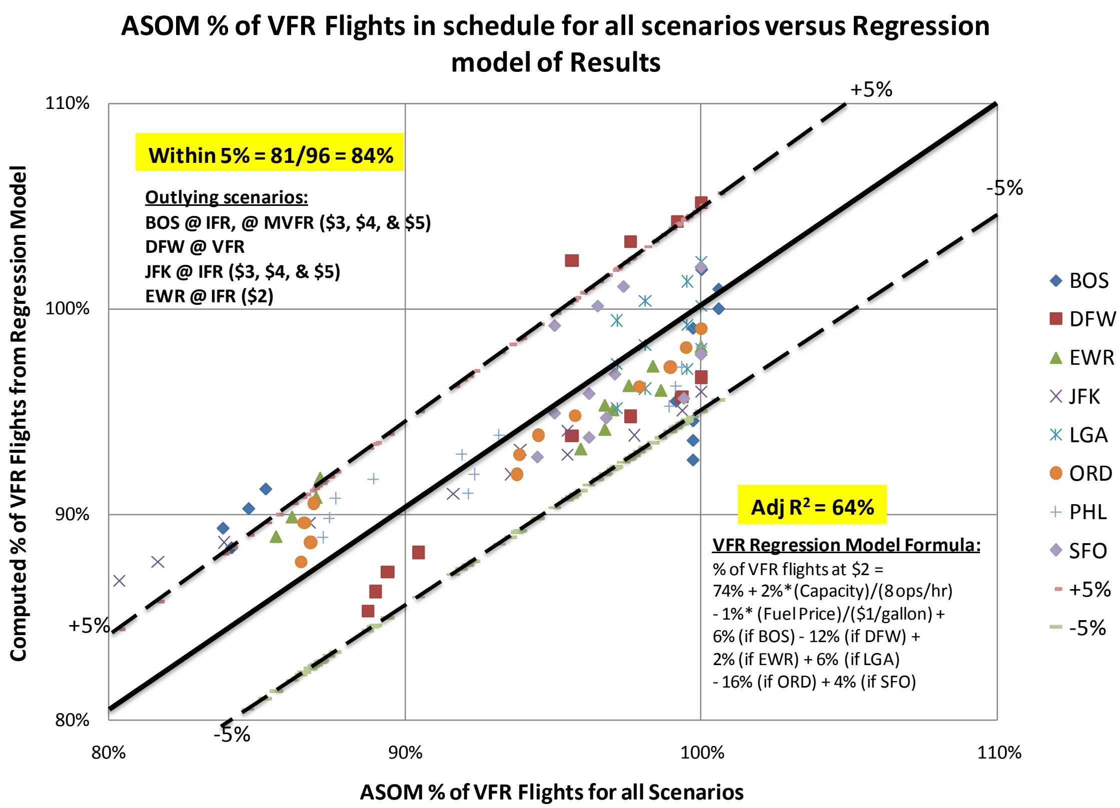



**Figure 42 Goodness of fit of the model of daily flights in ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

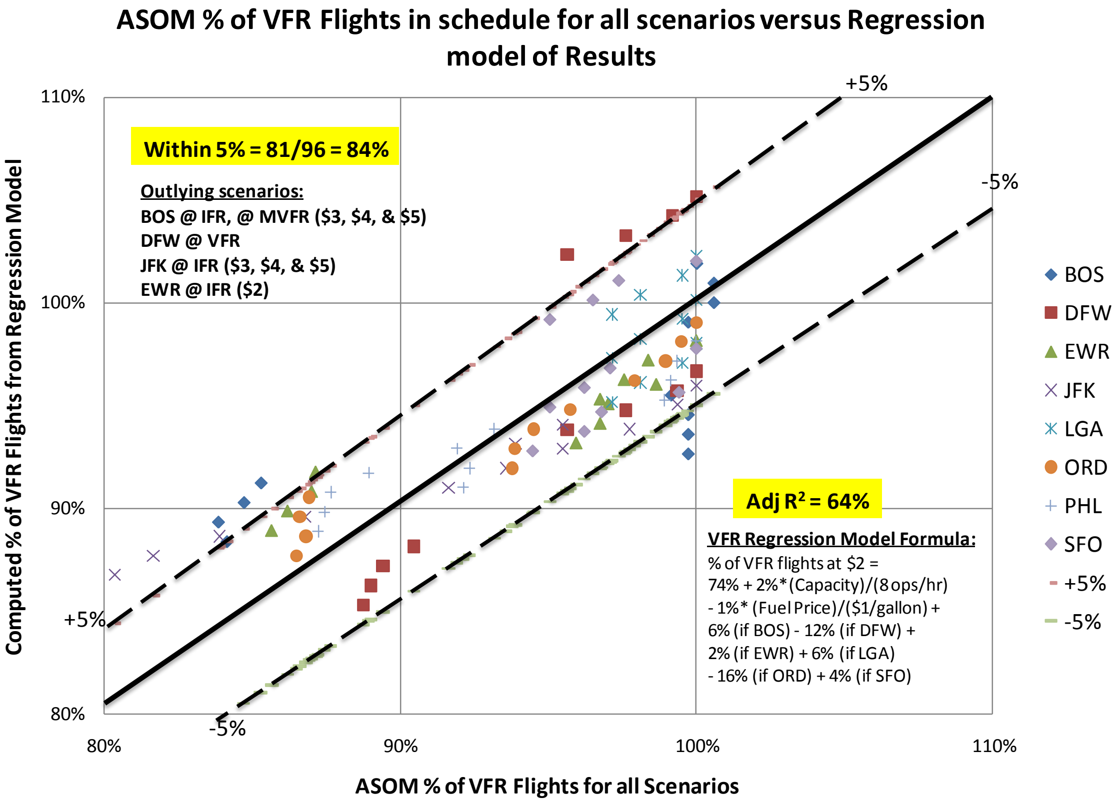



Figure 42 provides a goodness of fit analysis for the model of flights in the schedule as a percentage of flights in the schedule at VFR capacity limits and at $2 fuel prices. This model describes flights in the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of VFR flights at $2** = 74% + 2%*(Capacity)/(8 ops/hr) - 1%* (Fuel Price)/($1/gallon) + 6% (if BOS) - 12% (if DFW) + 2% (if EWR) + 6% (if LGA) - 16% (if ORD) + 4% (if SFO)

This model failed to compute 15 of the 96 ASOM scenarios used to derive this model within 5% of the ASOM values. All four of the BOS scenarios for IFR runway capacity limits scenarios, three of the four ($3, $4, and $5) BOS scenarios at MVFR runway capacity limits, all four of the DFW scenarios for VFR runway capacity limits, three of the four ($3, $4, and $5) JFK scenarios at IFR runway capacity limits, and the EWR scenario at IFR runway capacity limits and $2 fuel prices.

#### *5.3.3.2. Model of Passenger Demand served in the daily schedule as a percentage of Passenger Demand served in VFR schedules at $2 fuel prices*

Figure 43 provides a goodness of fit analysis for the model of passenger demand served in the schedule as a percentage of passenger demand served in the schedule at VFR capacity limits and at $2 fuel prices. This model describes passenger demand served in the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of VFR passenger demand at $2** = 105% + 1%*(Capacity)/(8 ops/hr)

- 9%* (Fuel Price)/($1/gallon) - 7% (if DFW) - 2% (if JFK) + 4% (if LGA) - 9% (if ORD)

- 2% (if PHL)

This equation modeled 86 of the 96 ASOM scenarios within 5% of the ASOM values. The ten scenarios outside of 5% include three of the four ($2, $3, and $4) JFK scenarios at IFR runway capacity limits, JFK scenarios at MVFR and VFR for $5 fuel prices, the DFW scenario at IFR runway capacity limits and $5 fuel prices, the DFW scenario at VFR runway capacity limits and $3 fuel prices, LGA scenarios at MVFR and IFR for $5 fuel prices, and the EWR scenario at IFR runway capacity limits and $3 fuel prices.

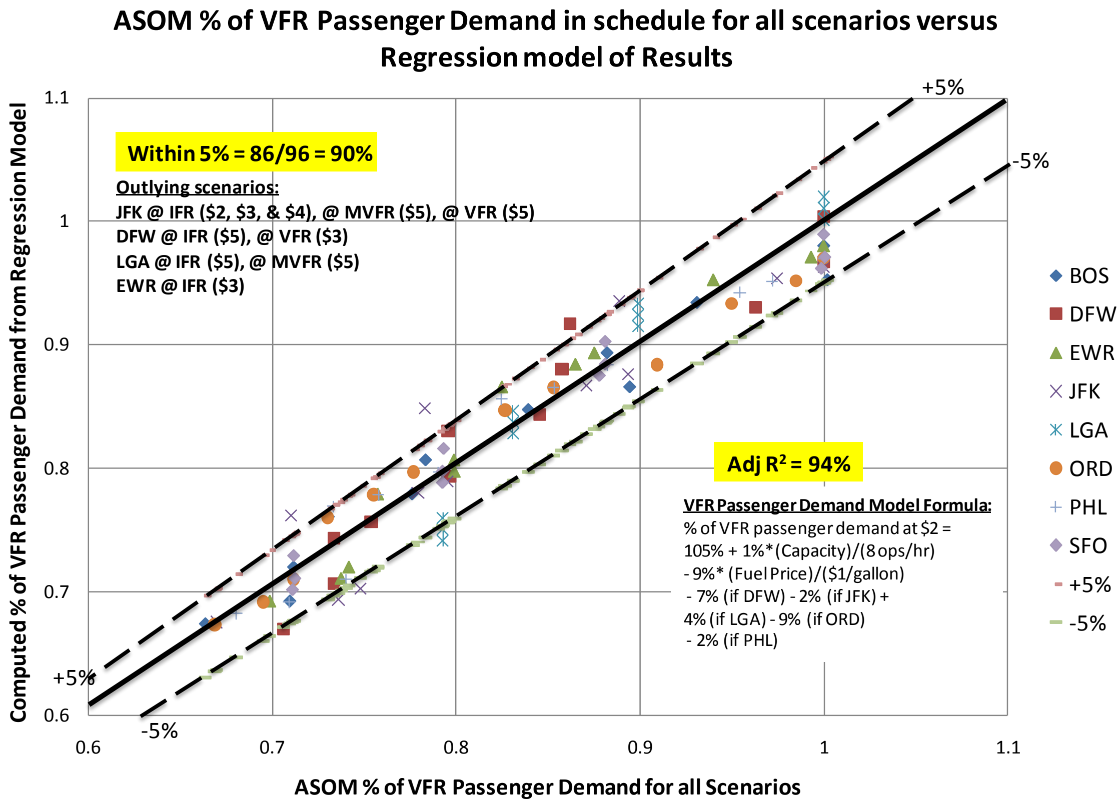



**Figure 43 Goodness of fit of the model of passenger demand served in ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

#### *5.3.3.3. Model of Average Airfare from the daily schedule as a percentage of Average Airfare from VFR schedules at $2 fuel prices*

Figure 44 provides a goodness of fit analysis for the model of average airfare from the schedule as a percentage of average airfare from the schedule at VFR capacity limits and at $2 fuel prices. This model describes average airfare from the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of average airfare from VFR schedules at $2 =**

68% - 0.4%*(Capacity)/(8 ops/hr) + 19%* (Fuel Price)/($1/gallon) + 2% (if DFW)

- 3% (if JFK)- 5% (if LGA) + 3% (if ORD) - 2% (if SFO)

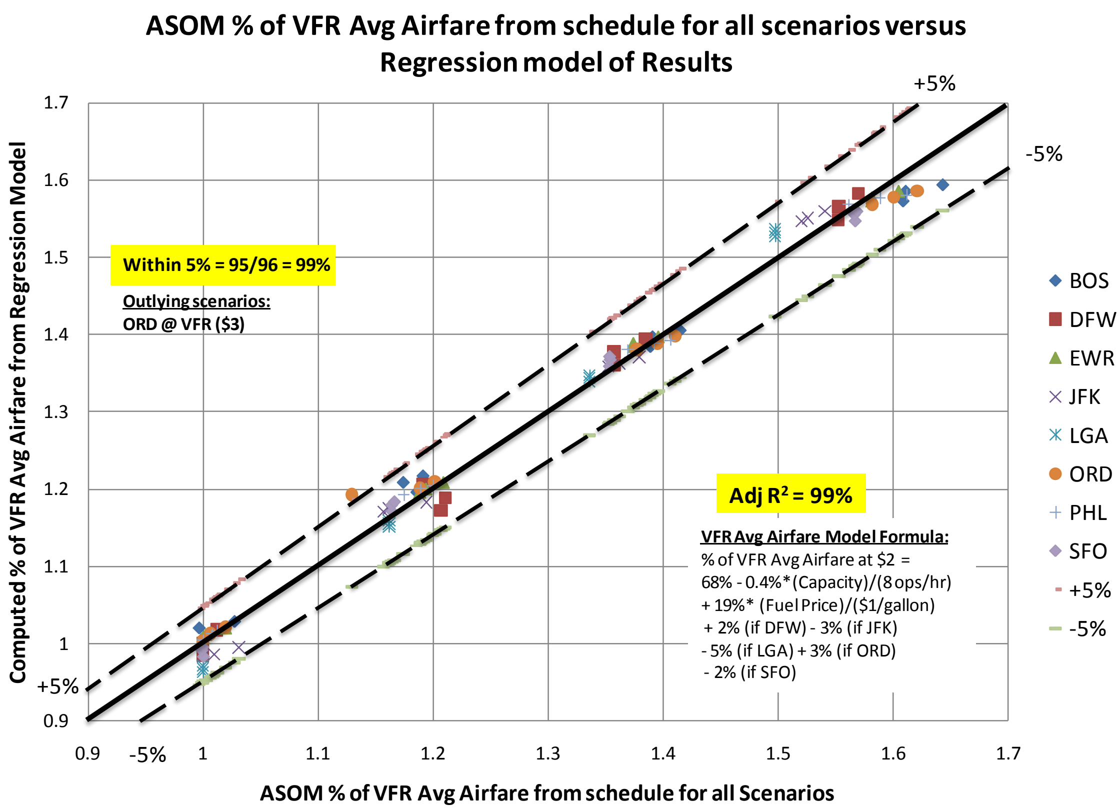



**Figure 44 Goodness of fit of the model of average airfare from the ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

This model failed to compute 1 of the 96 ASOM scenarios used to derive this model within 5% of the ASOM values, the ORD scenario at VFR runway capacity limits and $3 fuel prices.

#### *5.3.3.4. Model of Airline Profits from the daily schedule as a percentage of Airline Profits from VFR schedules at $2 fuel prices*

Figure 45 provides a goodness of fit analysis for the model of airline profits from the schedule as a percentage of airline profits from the schedule at VFR capacity limits and at $2 fuel prices. This model describes airline profits from the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of airline profits from VFR schedules at $2 =**

105% - 3%* (Fuel Price)/($1/gallon) +2% (if BOS) - 7% (if JFK) + 5% (if LGA) - 3% (if SFO)

This equation modeled 84 of the 96 ASOM scenarios within 5% of the ASOM values. The twelve scenarios outside of 5% include three of the four ($2, $3, and $4) JFK scenarios at IFR runway capacity limits, the JFK scenarios at MVFR and VFR for $2 fuel prices, the SFO scenarios at IFR, MVFR and VFR for $2 fuel prices, the LGA scenarios at IFR, MVFR and

VFR for $5 fuel prices, and the PHL scenario at IFR runway capacity limits and $3 fuel prices.

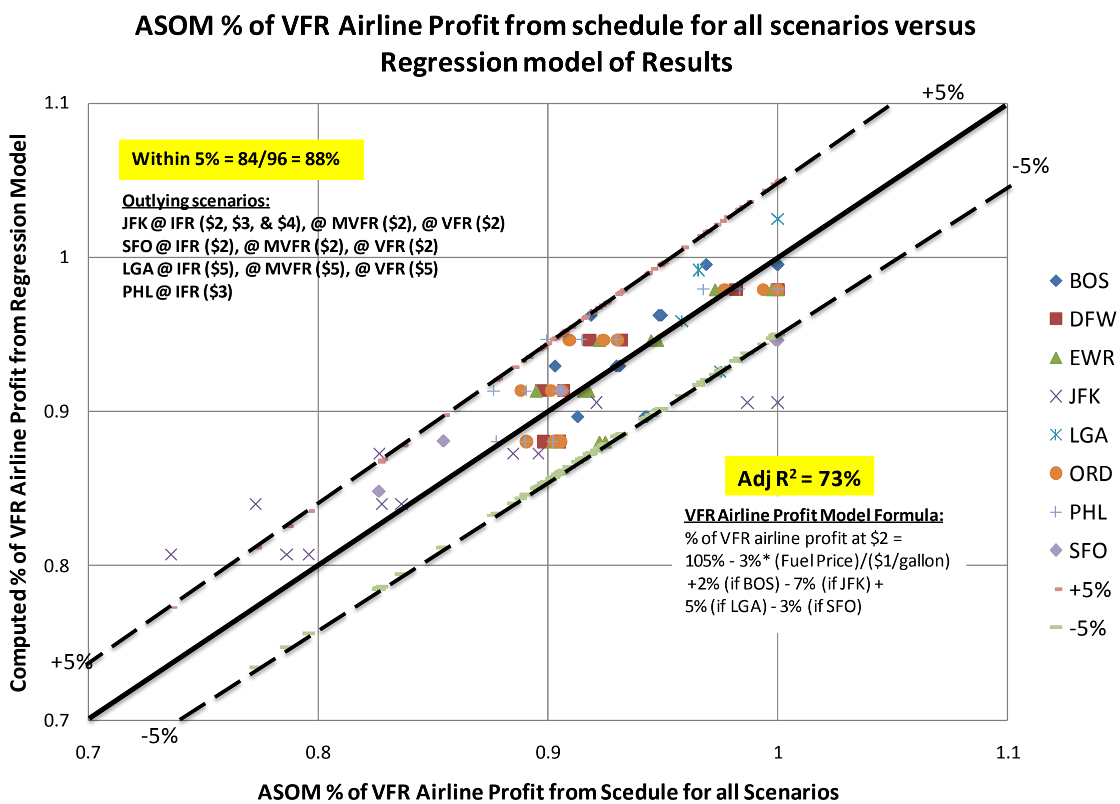



**Figure 45 Goodness of fit of the model of airline profit from the ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

### *5.3.3.5. Model of Fuel Burn from the daily schedule as a percentage of Fuel Burn from VFR schedules at $2 fuel prices*

Figure 46 provides a goodness of fit analysis for the model of fuel burn from the schedule as a percentage of fuel burn from the schedule at VFR capacity limits and at $2 fuel prices. This model describes fuel burn from the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of fuel burn from VFR schedules at $2 =**

106% + 1%*(Capacity)/(8 ops/hr) - 8%* (Fuel Price)/($1/gallon) - 6% (if DFW)

+ 3% (if LGA) - 9% (if ORD) - 2% (if PHL)

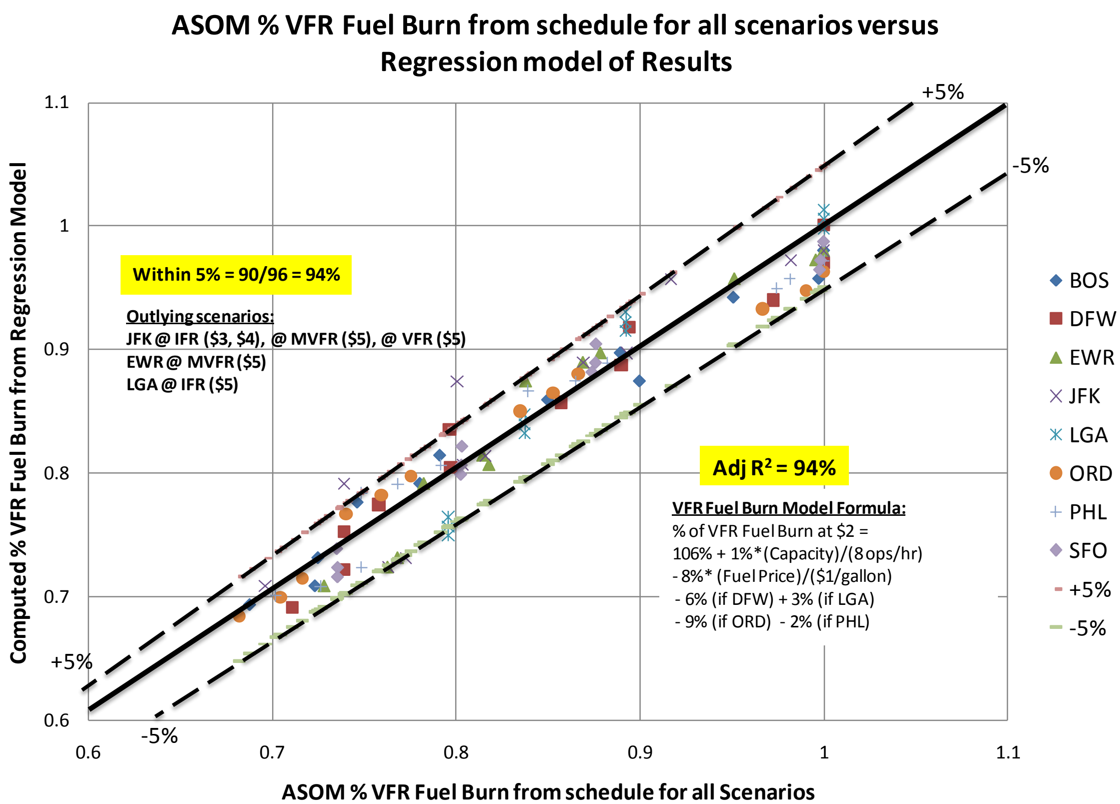



**Figure 46 Goodness of fit of the model of fuel burn from the ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

This equation modeled 90 of the 96 ASOM scenarios within 5% of the ASOM values. The six scenarios outside of 5% include two of the four ($3, and $4) JFK scenarios at IFR runway capacity limits, the JFK scenarios at MVFR and VFR for $5 fuel prices, the EWR scenario at MVFR runway capacity limits and $5 fuel prices, and the LGA scenario at IFR runway capacity limits and $5 fuel prices.

#### *5.3.3.6. Model of Average Aircraft Size from the daily schedule as a percentage of Average Aircraft Size from VFR schedules at $2 fuel prices*

Figure 47 provides a goodness of fit analysis for the model of average aircraft size from the schedule as a percentage of average aircraft size from the schedule at VFR capacity limits and at $2 fuel prices. This model describes average aircraft size from the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of average aircraft size from VFR schedules at $2 =**

128% - 1%*(Capacity)/(8 ops/hr) - 8%* (Fuel Price)/($1/gallon) - 3% (if BOS) +

7% (if DFW) + 7% (if ORD) - 2% (if SFO)

This equation modeled 86 of the 96 ASOM scenarios within 5% of the ASOM values. The ten scenarios outside of 5% include two of the four ($4, and $5) BOS scenarios at MVFR runway capacity limits, the BOS scenario at IFR runway capacity limits and $2 fuel prices, the LGA scenarios at IFR, MVFR and VFR for $5 fuel prices, the JFK scenarios at MVFR and VFR for $5 fuel prices, the DFW scenario at VFR runway capacity limits and $5 fuel prices, and the ORD scenario at IFR runway capacity limits and $2 fuel prices.

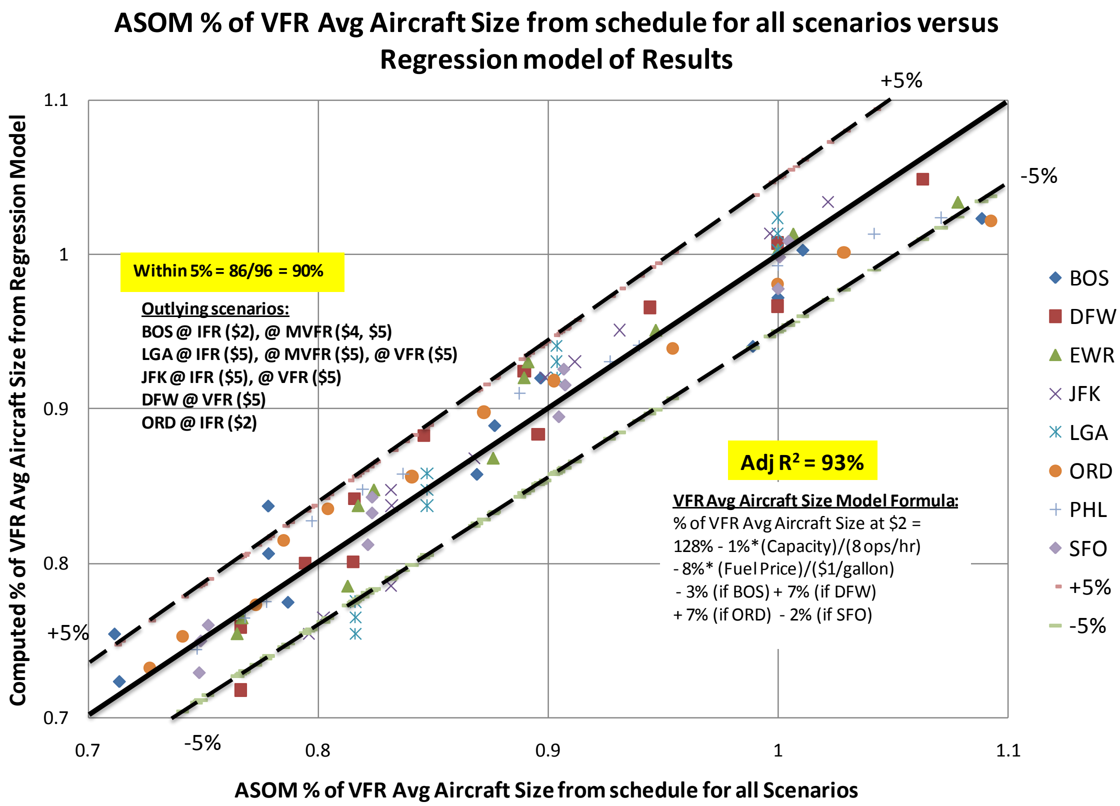



**Figure 47 Goodness of fit of the model of average aircraft size from the ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

#### *5.3.3.7. Model of Available Seat Miles from the daily schedule as a percentage of Available Seat Miles from VFR schedules at $2 fuel prices*

Figure 48 provides a goodness of fit analysis for the model of available seat miles from the schedule as a percentage of available seat miles from the schedule at VFR capacity limits and at $2 fuel prices. This model describes available seat miles from the schedule as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study, as shown below:

**Percentage of available seat miles from VFR schedules at $2 =**

108% + 1%*(Capacity)/(8 ops/hr) - 9%* (Fuel Price)/($1/gallon) - 3% (if DFW)

+ 1% (if EWR) + 4% (if LGA) - 6% (if ORD)

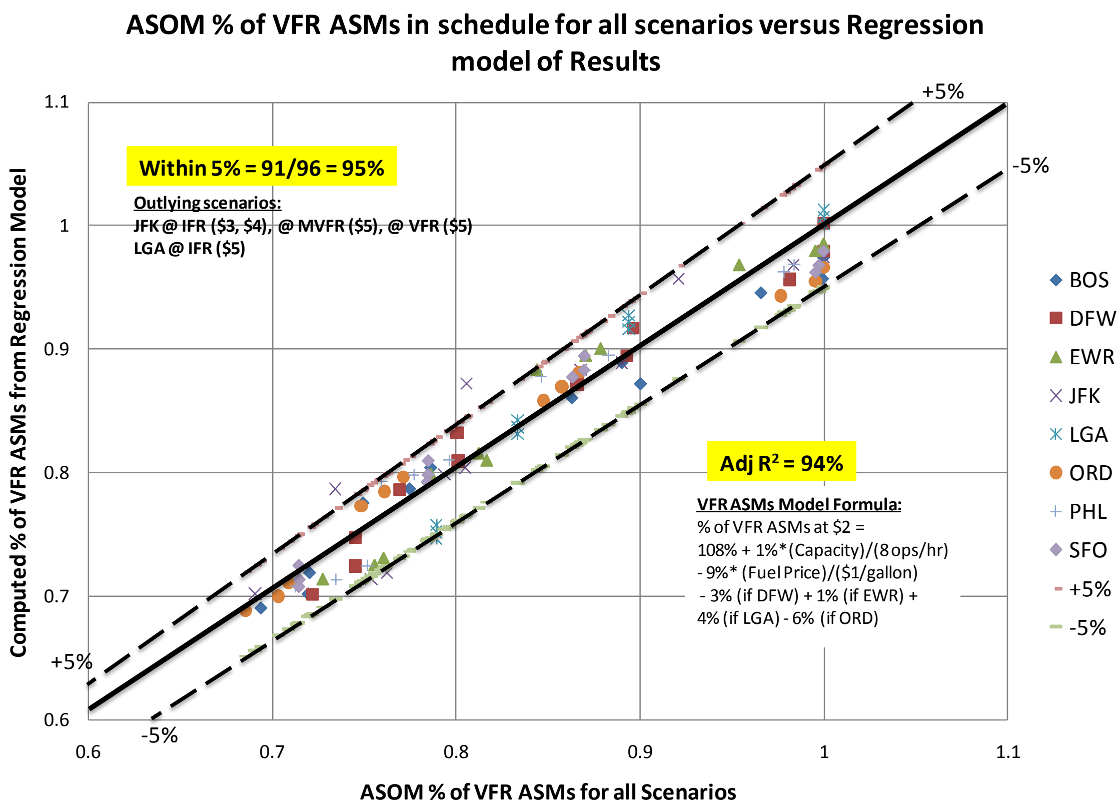



**Figure 48 Goodness of fit of the model of available seat miles from the ASOM schedules as a function of airport runway capacity (ops/hr), fuel price ($/gal), and airports examined in this study**

This equation modeled 91 of the 96 ASOM scenarios within 5% of the ASOM values. The five scenarios outside of 5% include two of the four ($3, and $4) JFK scenarios at IFR runway capacity limits, the JFK scenarios at MVFR and VFR for $5 fuel prices, and the LGA scenario at IFR runway capacity limits and $5 fuel prices.

### 5.4. Summary of Results

The objective of this research is to inform decision-makers on how changes in airport capacity, increased airline operational costs (such as fuel prices), and aircraft performance (fuel burn rates) impact geographic access to air transportation service. By examining how airlines add or drop markets and change frequency of daily flights this research will be able to answer the following questions: (1) What happens to geographic access to air transportation services by congestion management schemes such as "caps" at certain highly-congested airports? Would such regulations result in an elimination of service at smaller markets, impact the number of passengers served, the average airfare charged for service to daily markets, and/ or the profitability of airlines? (2) Would increased operational costs from fuel prices reduce or eliminate service to smaller markets. How would changes in airline scheduling impact the number of passengers served, the average airfare charged, and the profitability of airlines?

This dissertation shows statistically significant impacts on airline schedules from increased operational costs (increased fuel prices) and from reduced flight capacity at the airports (reduced operations per hour). Specifically markets served, flights scheduled, passengers scheduled, average revenue/ seat charged, airport aggregate daily profit, average aircraft size (seats/flight) in schedule, aggregate daily fuel burn, and available seat miles (ASMs) in the schedule were examined.

The following analysis will summarize the findings from the ASOM on the effects of reduced capacity limits and increased fuel prices on congested airports.

### 5.4.1. Reduced Capacity Effects on Congested Airports

Table 33 summarizes the effects of reduced capacity limits on schedules at congested airports. This analysis shows a comparison of the aggregate schedule impacts from reductions in airport flight capacity from visual flight rules (VFR) to marginal visual flight rules (MVFR), from reductions in airport flight capacity from MVFR to instrument flight rules (IFR), and the coefficient from a market level regression analysis on each airport metric. As shown in Table 33, the number of markets in the analysis was not examined with a market level regression analysis, however only 1% of the markets served were lost when reducing the airport flight capacity from VFR to IFR. Airport flight capacity was found to statistically improve all models examined except for daily aggregate airport profit, based upon the t-test at a 90% level of confidence.

**Table 33 Summary of effects of decreased runway capacity (8 ops/hour) on congested airports**

| Statistical Impact on Airport Schedules | Decrease in Runway Capacity (8 ops/hr) | | |
|---|---|---|---|
| | VFR to MVFR | MVFR to IFR | Regression Analysis Coefficient |
| Markets | -1% | | n/a |
| Flights | -1% | -4% | -2% |
| Passengers | 0% | -2% | -1% |
| Revenue/ Seat | 0% | +1% | +0.4% |
| Daily Profit | 0% | -1% | Not statistically significant |
| average aircraft size (seats/flight) | +1% | +2% | -1% |
| Available seat miles (ASMs) | 0% | -1% | -1% |
| Fuel burn | 0% | -1% | -1% |

This analysis shows that the all of the following hypotheses can be rejected. Reduction in runway capacity limits will

- reduce Markets Served at the airport
- reduce frequency of service for markets served at the airport
- reduce passengers served
- increase airfares
- reduce airline profitability at the airport
- increase available seat miles in the schedule

- reduce fuel burn

### 5.4.2. Increased Fuel Price Effects on Congested Airports

Table 34 summarizes the effects of increased fuel prices on schedules at congested airports. This analysis shows a comparison of the aggregate schedule impacts from increases in airline fuel costs from $2 per gallon to $3 per gallon, from $3 per gallon to $4 per gallon, from $4 per gallon to $5 per gallon, and the coefficient from a market level regression analysis on each airport metric. As shown in Table 34, the number of markets in the analysis was not examined with a market level regression analysis, however only 1% of the markets served were lost when fuel costs increased from $2 to $5 per gallon. Fuel cost was found to statistically improve all models examined, based upon the t-test at a 90% level of confidence.

**Table 34 Summary of effects of increased fuel prices ($1/ gallon) on congested airports**

| Statistical Impact on Airport Schedules | $1 Increase in Fuel Prices | | | |
|---|---|---|---|---|
| | $2 to $3 | $3 to $4 | $4 to $5 | Regression Analysis Coefficient |
| Markets | -1% | | | n/a |
| Flights | -1% | -1% | -1% | -1% |
| Passengers | -11% | -11% | -8% | -9% |
| Revenue/ Seat | +17% | +17% | +14% | +19% |
| Daily Profit | -7% | -3% | 0% | -3% |
| average aircraft size (seats/flight) | -11% | -9% | -7% | -8% |
| Available seat miles (ASMs) | -12% | -10% | -7% | -9% |
| Fuel burn | -12% | -10% | -7% | -8% |

This analysis shows that increased fuel costs will:

- reduce Markets Served at the airport
- reduce frequency of service for markets
- reduce airline profitability at the airport
- reduce passengers served
- reduce fuel burn
- increase airfares
- cause the airlines to increase aircraft size
- increase available seat miles in the schedule

### 5.4.3. Trade off between fuel price increases and reduced capacity limits

When comparing the coefficients from the regression analysis of the 96 scenarios or schedules, a trade-off analysis can be made for fuel price changes versus runway capacity reductions. Table 35 show the equivalent change in fuel price required to offset a reduction in runway capacity of one operation per hour. Airline profit was not found to have a significant statistical relationship with runway capacity, so a trade-off analysis cannot be made for airline profits. Five of the remaining metrics (passenger demand served, ASMs, fuel burn, average airfare, and average aircraft size) were found to be much more sensitive to fuel price changes than runway capacity changes, with average airfare being the most sensitive. On the other hand, a $1 increase in fuel prices reduces an equivalent amount of flights from the schedule as a reduction of 4 operations per hour in runway capacity.

**Table 35 the required increase in fuel price for equivalent effects from reduction of 1 operation per hour in runway capacity**

| Increase in Fuel Price for Equivalent effect of reduction of 1 op/hr | | | | | | |
|---|---|---|---|---|---|---|
| flights | demand | ASMs | Profit | Fuel Burn | avg Airfare | seats/flight |
| $0.28 | $0.01 | $0.01 | N/A | $0.01 | $0.003 | -$0.02 |

### 5.4.4. Analysis of markets removed from schedule due to increases in aviation fuel prices when operating at MVR capacity

Figure 49 illustrates markets which were dropped from the schedules when aviation fuel prices were increased. The first column indicates the originating airport and column three shows the destination airport for these markets. The second column indicates at what aviation fuel price the market was dropped from the schedule. Overall 26 markets were dropped when aviation fuel prices were raised from $2 to $5 for MVFR schedules. Of these markets 14 of the 26 have been reduced or eliminated since 3rd quarter 2007. Only three of these markets have increased flight frequencies since 3rd quarter 2007.

| Airport | Fuel Price | market | 3QTR 2007 departures | 3QTR 2009 departures | 3QTR 2010 departures | % change |
|---|---|---|---|---|---|---|
| BOS | 3 | MEM | 466 | 435 | 442 | -5% |
| | 4 | DAY | 64 | 1 | 1 | -98% |
| | 4 | PQI | 245 | 247 | 247 | 1% |
| | 5 | BGR | 638 | 179 | 12 | -98% |
| DFW | 3 | HNL | 181 | 200 | 182 | 1% |
| | 3 | CLL | 388 | 271 | 269 | -31% |
| | 3 | MLU | 255 | 265 | 270 | 6% |
| EWR | 3 | BGR | 120 | 57 | 1 | -99% |
| | 4 | OMA | 248 | 238 | 241 | -3% |
| JFK | 4 | SRQ | 91 | 161 | 92 | 1% |
| LGA | 3 | PHL | 780 | 1074 | 1629 | 109% |
| | 3 | MHT | 533 | 319 | 316 | -41% |
| | 3 | BTV | 492 | 508 | 343 | -30% |
| | 3 | PVD | 358 | 278 | 204 | -43% |
| | 3 | CHO | 199 | 180 | 222 | 12% |
| | 3 | DSM | 91 | 69 | 57 | -37% |
| | 5 | CAE | 137 | 72 | 74 | -46% |
| ORD | 3 | SJU | 336 | 191 | 237 | -29% |
| PHL | 3 | ERI | 239 | 258 | 265 | 11% |
| | 4 | LGA | 962 | 1303 | 1771 | 84% |
| | 4 | OAK | 191 | 40 | 25 | -87% |
| | 5 | HVN | 400 | 397 | 394 | -2% |
| SFO | 4 | AUS | 97 | 186 | 279 | 188% |
| | 4 | CVG | 260 | 250 | 237 | -9% |
| | 5 | MEM | 231 | 220 | 140 | -39% |
| | 5 | IND | 79 | 2 | 2 | -97% |

**Figure 49 Analysis of markets removed from schedule due to increases in aviation fuel prices when operating at MVR capacity**

# CHAPTER 6 – CONCLUSIONS, INSIGHTS, AND FUTURE WORK

This analysis provides a model for how passenger demand versus airfare curves responds to economic changes in aviation fuel prices and unemployment rates. This mathematical model was incorporated into an airline scheduling equilibrium model that maximizes profit for a given airport, given changes in economic conditions (aviation fuel prices) and changes in airport flight capacity. This model provides a methodology for evaluating economic and policy impacts on airline and passenger behavior.

Additionally this analysis provided an understanding of how aircraft economics impact the size of aircraft airlines select to fly their schedules. Specifically increased operational costs may not lead to up gauging, depending on aviation fuel prices.

## 6.1. Conclusions

This analysis shows that reductions in runway capacity limits at a given airport will cause airlines to reduce schedules for markets served at this airport, reduce frequency of service for these markets, reduce passengers flown to these markets, and reduce available seat miles in the schedule. Additionally the airlines will increase airfares, increase average aircraft size, reduce fuel burn, and the airlines profits will be reduced. The analysis of the outputs from the ASOM model for the analysis described in chapter 5 of this dissertation found all of these affects from the reduction in runway capacity limits or airport flight capacity to be statistically significant.

This analysis shows that increased aviation fuel prices will cause airlines to reduce schedules for markets served at this airport, reduce frequency of service for these markets, reduce passengers flown to these markets, reduce available seat miles in the schedule, and reduce the average aircraft size used in the schedule. Additionally the airlines will increase airfares, reduce fuel burn, and the airlines profits will be reduced. The analysis of the outputs from the ASOM model for the analysis described in chapter 5 of this dissertation found all of these affects from increased aviation fuel prices to be statistically significant.

The impacts of fuel price increases and runway capacity limits on these aggregate domestic airline schedules are examined through changes in markets served, frequency of service, available seat miles, passengers served, average airfares for this service, daily airline profits and daily fuel burn. The results of this analysis show:

i. Current aircraft burn rates lack the economies of scale to incentivize up gauging by the airlines when fuel prices increase.

ii. Airlines can maintain profitable and affordable service for domestic markets when runway capacity limits are reduced.

iii. Increases in fuel prices (+$1/gallon) results in significant down gauging (-8%), reduced service (-9% ASMs) for domestic markets and increased airfares (+19%).

iv. Increases in fuel price (+$1/gallon) reduce passenger price elasticity (-13%) for domestic air transportation.

The caveats of these findings are without changes in aircraft performance (fuel burn rates); increasing runway slot productivity (i.e. more seats per operation) will not occur. Reductions in runway capacity limits at congested airports can be achieved without risk of reduced airline profits, eliminated service to domestic markets, and increased airfares for passengers. Increases in fuel prices will cause airlines to reduce service to domestic markets, increase airfares, and operate with losses until fleets can be down gauged. Lastly, future economic analysis of air transportation must address the sensitivity of passenger demand versus airfare curves to economic fluctuations.

The findings of this dissertation are supported by a study conducted by the Department of Transportation's Bureau of Transportation Statistics. (Firestine & Guarino 2012) This report confirms the findings of this dissertation on how airline fuel costs have started to dominate airline operational costs. Additionally, this report identifies the impact of aviation fuel price increases on airline schedules. Specifically this report illustrates how available seat miles in domestic schedules dropped as aviation fuel prices were increasing in 2008.

The findings of this dissertation are also supported by a study conducted by the Reason Foundation. (Poole 2012) This study indicates that earlier forecasts predicting 100% to 200% growth in the next twenty years were considerably off. This slower growth of the national air transportation system is directly associated with the economic factors identified in this dissertation.

## 6.2. Insights

This analysis found that the less profitable markets to smaller or economically depressed communities were the first to be dropped from the schedule when aviation fuel prices were increased or when airport flight capacity was reduced. Appendix B of this dissertation illustrates this behavior for Philadelphia International Airport. The markets that require Essential Air Service (EAS) were not modeled in the airline scheduling equilibrium model, since these are not profitable markets for the airlines in absence of EAS funds.

The demand versus airfare curves for markets were sensitive to changes in economic factors. These curves adjusted as aviation fuel prices increased to account for the willingness of the passengers to fly at higher airfares.

Multiple stakeholders for the US air transportation system can benefit from an understanding of airline and passenger behavior in the presence of economic and regulatory changes. This research provides a methodology and model (the ASOM) to examine these airline and passenger behaviors.

Government policy-makers will be provided a quantitative analysis of impact of changes to airline scheduling and pricing behavior that are likely to result from changes in airport capacity limits or with changes in fees.   This research provides a better understanding of aircraft economies of scale and how they change due to increased fuel prices

Airline economists are provided a methodology to examine passenger demand versus airfare curves as a function of seasonality, competition, frequency of service and economic factors.  These coefficients of change provide a good metric to compare an airport's sensitivity to economic changes

Airspace Researchers (e.g. NASA, Metron Aviation, Sensis, FAA) will be able to use this tool to see if new technologies (e.g. better separation rates, aircraft with better fuel or emissions efficiency) will significantly impact the number and type of passengers using the airspace as well as the predicted delays that such schedules might create.

## 6.3. Future Work

Analysis of airline behavior with the ASOM is computationally intensive.  Automation of the preprocessing for the ASOM would significantly reduce the turnaround time for ASOM analysis.  Development of heuristics for the ASOM sub problem could significantly reduce the ASOM computation time.

Connecting passengers demand versus airfare curves is significantly different than curves for direct non-stop passengers. Modeling these passengers separately could significantly improve the accuracy of the model.

The ASOM models the non-stop direct domestic markets at an aggregate level with many assumptions that are global in the model. Modeling individual market load factors and turnaround times for connecting flights would improve the fidelity of the model.

The ASOM models airline scheduling behavior for all non-stop domestic markets at an airport while leaving the international markets fixed. Future analysis should consider modeling these international markets along with the domestic markets. Future analysis should also consider modeling all domestic markets at the airport, non-stop and connecting.

The ASOM models the impact of changes in fuel prices on airline scheduling behavior, while leaving non-fuel related operational costs constant. Future analysis should examine the impact of fluctuations in non-fuel related operational costs on airline scheduling behavior. Since non-fuel related operational costs showed economies of scale, restructured landing fees or congestion pricing might incentivize the airlines to up gauge to avoid congestion.

## APPENDIX A – ANALYSIS OF THE IMPACTS OF CAPACITY AND FUEL PRICE ON AIRLINE SCHEDULING BEHAVIOR

To better understand the impacts of capacity limits and fuel price increases on airline scheduling and passenger demand behavior, this analysis examines the 595 markets which are present in all scenarios.

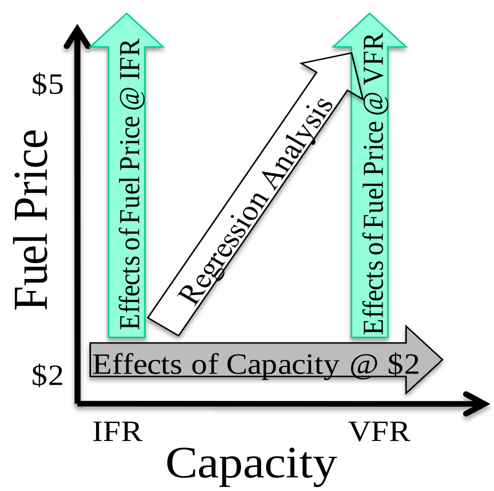



**Figure 50 Analysis roadmap**

Over the next four sections the effects of capacity and fuel price on frequency of service, passenger demand, average airfare, airline profitability, aviation fuel burn, average aircraft size or seats per operation and available seat miles for schedules produced for different scenarios for the 595 markets that remain in all scenarios at the eight airports examined. As shown in Figure 50, first the effects of capacity will be examined at constant $2 fuel prices, next the effects of fuel price will be examined at VFR capacities and then at IFR capacities and then a regression analysis will look at the effects both capacity and fuel price have on the metrics of interest.

## A.1 Impact of Runway Capacity Limits on Airline Scheduling and Passenger Demand Behavior

The effects of capacity limits for the 595 markets which remain in the aggregated schedule for all scenarios are presented in this section. These markets are examined to evaluate effects from reducing runway capacity limits from VFR to MVFR and MVFR to IFR, with fuel prices fixed at $2 per gallon. Due to the peaked nature of most airport operations, reductions of capacities from VFR to MVFR have much less effect compared to reductions of capacities from MVFR to IFR as shown in Figure 51.

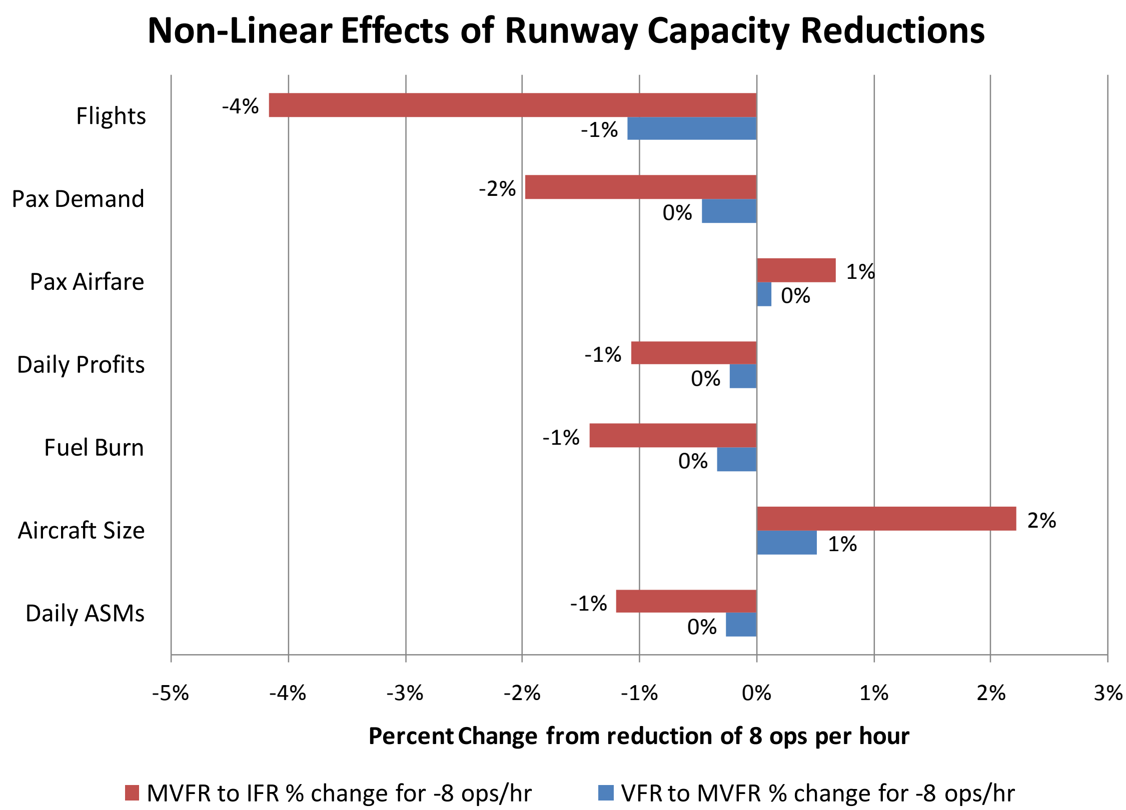



**Figure 51  Non-linear effects from runway capacity reductions**

Table 36 shows the impact of reduced 8 operations per hour as a percentage of VFR or MVFR capacity levels at the eight airports examined in this study.  On average all eight airports capacity are reduced -7% from a reduction of 8 operations per hour at VFR capacity levels and -9% from a reduction of 8 operations per hour at MVFR capacity levels.  Figure 51 shows that this reduction of 7% in capacity at VFR capacity levels effects only one metric more than 1%, flights are reduced more than 1%.  And the reduction of 9% in capacity at MVFR capacity levels effects three metrics more than 2%, flights are reduced more than 4%, passenger demand is reduced 2%, and aircraft size is increased more than 2%. This reduction in schedule combined with up-gauging (increase in aircraft size) is desired effects for the system, but are only realized with significant reductions in current runway operational capacities to levels below MVFR rates.

**Table 36 Relative impact from a reduction of 8 operations per hour in capacity**

| **Airports** | **VFR+** | **% change from -8 ops/hr** | **MVFR** | **% change from -8 ops/hr** |
|---|---|---|---|---|
| BOS | 88 | **-9%** | 64 | **-13%** |
| DFW | 168 | **-5%** | 136 | **-6%** |
| EWR | 88 | **-9%** | 80 | **-10%** |
| JFK | 88 | **-9%** | 80 | **-10%** |
| LGA | 88 | **-9%** | 80 | **-10%** |
| ORD | 160 | **-5%** | 144 | **-6%** |
| PHL | 96 | **-8%** | 80 | **-10%** |
| SFO | 96 | **-8%** | 80 | **-10%** |
| **Total** | **872** | **-7%** | **744** | **-9%** |

The effects of reductions in capacity are not uniform across airport capacity levels and are not uniform across airports, as shown in Table 37. DFW, LGA and SFO show practically no effects from reduced capacity limits; however the other airports show greater effects. Little effects are seen from reduction in capacity from MVFR to IFR. The greatest reductions in flights, reduction in passenger demand and increased aircraft size is seen from reduction in capacity from MVFR to IFR.

**Table 37 Airport analysis of the effects from capacity limit reductions**

| Geographis Access | | | | | | | Economic Access | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Markets Served | | | | Flights per Day | | | Passenger Demand | | Average Airfare | |
| VFR | MVFR | IFR | % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | Airports | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| Analysis for Markets in schedule at IFR capacity and $5 fuel price | | 56 | N/A | 0% | -7% | BOS | 0% | -4% | 0% | 2% |
| | | 115 | N/A | 0% | -2% | DFW | 0% | -1% | 0% | 0% |
| | | 70 | N/A | -1% | -6% | EWR | -1% | -3% | 0% | 1% |
| | | 47 | N/A | -2% | -6% | JFK | -3% | -4% | 1% | 1% |
| | | 57 | N/A | 0% | 0% | LGA | 0% | 0% | 0% | 0% |
| | | 121 | N/A | -2% | -5% | ORD | -1% | -2% | 0% | 1% |
| | | 76 | N/A | -3% | -5% | PHL | -1% | -2% | 0% | 0% |
| | | 53 | N/A | 0% | -1% | SFO | 0% | 0% | 0% | 0% |

| | Airline Profitability | | | ATS Efficiency | | | | | Environmental Impact | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Profits | | | Average Aircraft Size | | Daily ASMs (Millions) | | | Daily Fuel Burn | |
| | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | Airports | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | Airports | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| | 0% | -2% | BOS | 0% | 4% | 0% | -2% | BOS | 0% | -2% |
| | 0% | 0% | DFW | 0% | 2% | 0% | 0% | DFW | 0% | -1% |
| | 0% | -1% | EWR | 1% | 4% | 0% | -2% | EWR | 0% | -2% |
| | -1% | -3% | JFK | 0% | 1% | -2% | -3% | JFK | -2% | -3% |
| | 0% | 0% | LGA | 0% | 0% | 0% | 0% | LGA | 0% | 0% |
| | 0% | -1% | ORD | 1% | 3% | 0% | -1% | ORD | 0% | -1% |
| | -1% | -2% | PHL | 2% | 3% | -1% | -1% | PHL | -1% | -1% |
| | 0% | 0% | SFO | 0% | 0% | 0% | 0% | SFO | 0% | 0% |

Evaluating the effects of capacity by market distance, the effects vary greatly as shown in Table 38. Since 79% of the flights are for markets from 125 to 1125 miles from the airport, this is where the analysis is focused. As shown in previous analysis in this section the effects are greater from capacity reductions between MVFR and IFR capacity levels, than they are from capacity reductions between VFR and MVFR capacity levels. The 138 markets from 125 to 375 miles from the airports show the greatest effects from reduced capacity limits, when compared to other market distance bands. A reduction of

8 operation per hour between MVFR and IFR capacity levels for markets served between 125 and 375 miles of the airports cause a reduction of 14% of the scheduled flights, a reduction of 9% of the passengers served by the schedule, a 2% increase in airfares, a 6% reduction in profits, a 8% reduction in fuel burn, a 6% increase in aircraft size, and a 8% reduction in available seat miles.

The remaining 290 markets from 375 and 1125 miles from the airports show similar effects. A reduction of 8 operation per hour between MVFR and IFR capacity levels for markets served between 375 and 1125 miles of the airports cause a reduction of 6% of the scheduled flights, 2% of the passengers served by the schedule, a 3% reduction in fuel burn, a 3% increase in aircraft size, and a 2% reduction in available seat miles.

The 153 markets 1125 miles or more from the airports show minor effects and represent 20% of the flights in the airport schedules. A reduction of 8 operations per hour between MVFR and IFR capacity levels for markets served greater than 1125 miles from the airports cause a reduction of 2% of the scheduled flights

## Table 38 Market Distance analysis of the effects from capacity limit reductions

| | Geographis Access | | | | | Density of Flights | |
|---|---|---|---|---|---|---|---|
| | Markets Served | | | Flights per Day | | 79% | 79% |
| Market Distance (miles) | VFR/ MVFR | IFR | % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | % of VFR scheduled flights | % of IFR scheduled flights |
| <125 | Analysis for Markets in schedule at IFR capacity and $5 fuel price | 14 | N/A | -16% | -36% | 2% | 1% |
| 125-375 | | 138 | N/A | -4% | -14% | 28% | 26% |
| 375-625 | | 110 | N/A | -2% | -6% | 19% | 20% |
| 625-875 | | 106 | N/A | -1% | -6% | 19% | 20% |
| 875-1125 | | 74 | N/A | -1% | -5% | 12% | 12% |
| 1125-1375 | | 41 | N/A | -2% | -4% | 5% | 5% |
| 1375-1625 | | 36 | N/A | 0% | -2% | 5% | 6% |
| 1625-1875 | | 22 | N/A | 0% | -1% | 3% | 3% |
| 1875-2125 | | 8 | N/A | -4% | 0% | 1% | 1% |
| 2125-2375 | | 14 | N/A | -2% | -4% | 1% | 1% |
| 2375-2625 | | 29 | N/A | -1% | -2% | 4% | 4% |
| >2625 | | 3 | N/A | 0% | 0% | 0% | 0% |

| | Economic Access | | | | Airline Profitability | |
|---|---|---|---|---|---|---|
| | Passenger Demand | | Average Airfare | | Daily Profits | |
| Market Distance (miles) | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| <125 | -19% | -30% | -4% | -1% | -25% | -28% |
| 125-375 | -2% | -9% | 0% | 2% | -1% | -6% |
| 375-625 | -1% | -2% | 0% | 0% | 0% | -2% |
| 625-875 | 0% | -2% | 0% | 0% | 0% | -1% |
| 875-1125 | -1% | -3% | 0% | 1% | 0% | -1% |
| 1125-1375 | 0% | -2% | 0% | 0% | 0% | -1% |
| 1375-1625 | 0% | 0% | 0% | 0% | 0% | -1% |
| 1625-1875 | 0% | -1% | 0% | 0% | 0% | 0% |
| 1875-2125 | -1% | 0% | 0% | 0% | 0% | 0% |
| 2125-2375 | 0% | -4% | 0% | 1% | 0% | -1% |
| 2375-2625 | -1% | -1% | 0% | 0% | 0% | -2% |
| >2625 | 0% | 0% | 0% | 0% | 0% | 0% |

| | Environmental Impact | | ATS Efficiency | | | |
|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | Average Aircraft Size | | Daily ASMs (Millions) | |
| Market Distance (miles) | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| <125 | -22% | -32% | -3% | 8% | -19% | -29% |
| 125-375 | -2% | -8% | 2% | 6% | -1% | -8% |
| 375-625 | -1% | -3% | 1% | 3% | -1% | -2% |
| 625-875 | 0% | -3% | 1% | 4% | 0% | -2% |
| 875-1125 | -1% | -3% | 0% | 2% | -1% | -3% |
| 1125-1375 | 0% | -2% | 2% | 2% | 0% | -2% |
| 1375-1625 | 0% | 0% | 0% | 2% | -1% | 0% |
| 1625-1875 | 0% | 0% | 0% | 0% | 0% | 0% |
| 1875-2125 | -1% | 0% | 3% | 0% | -1% | 0% |
| 2125-2375 | 0% | -4% | 2% | 0% | 0% | -4% |
| 2375-2625 | -1% | -1% | 1% | 1% | -1% | -1% |
| >2625 | 0% | 0% | 0% | 0% | 0% | 0% |

The effects of reduced capacity by aircraft size (average seats per operation) vary greatly as shown in Table 39. Since more than 83% of the flights are flown by aircraft between 37 to 87 seats per operation and between 112 to 162 seats per operation, this is where the analysis is focused. As shown in previous analysis in this section the effects are greater from capacity reductions between MVFR and IFR capacity levels, than they are from capacity reductions between VFR and MVFR capacity levels.

**Table 39 Aircraft type/ class analysis of the effects from capacity limit reductions**

| | Geographis Access | | | Density of Flights | |
|---|---|---|---|---|---|
| | Markets Served | Flights per Day | | 83% | 85% |
| Aircraft Size (seats) | VFR/ MVFR/ IFR | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | % of VFR scheduled flights | % of IFR scheduled flights |
| 25 | Analysis for Markets in schedule at IFR capacity and $5 fuel price | -5% | -36% | 8% | 5% |
| 50 | | -9% | -16% | 12% | 10% |
| 75 | | -3% | -11% | 33% | 32% |
| 100 | | -7% | 11% | 1% | 1% |
| 125 | | 0% | 1% | 10% | 11% |
| 150 | | 1% | 0% | 28% | 32% |
| 175 | | 1% | 3% | 4% | 4% |
| 225 | | -3% | 0% | 1% | 1% |
| 250 | | 2% | 0% | 3% | 3% |
| 275 | | 0% | -23% | 0% | 0% |
| 300 | | 0% | -12% | 0% | 0% |
| 325 | | 0% | 0% | 0% | 0% |

| | Economic Access | | | | Airline Profitability | |
|---|---|---|---|---|---|---|
| | Passenger Demand | | Average Airfare | | Daily Profits | |
| Aircraft Size (seats) | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| 25 | -5% | -36% | -2% | 5% | -7% | -30% |
| 50 | -9% | -16% | 5% | 6% | -3% | -8% |
| 75 | -3% | -11% | 1% | 1% | -2% | -9% |
| 100 | -7% | 11% | 5% | 1% | -3% | 8% |
| 125 | 0% | 1% | 0% | -2% | 0% | -1% |
| 150 | 1% | 0% | 0% | 1% | 1% | 2% |
| 175 | 1% | 3% | 1% | 3% | 3% | 9% |
| 225 | -3% | 0% | 3% | 4% | 2% | 5% |
| 250 | 2% | 0% | -2% | 1% | -1% | 2% |
| 275 | 0% | -23% | 0% | 10% | -1% | -13% |
| 300 | 0% | -12% | -1% | 3% | -2% | -9% |
| 325 | 0% | 0% | -1% | 0% | -4% | -1% |

| | Environmental Impact | | ATS Efficiency | | | |
|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | Average Aircraft Size | | Daily ASMs (Millions) | |
| Aircraft Size (seats) | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr | VFR to MVFR % change for -8 ops/hr | MVFR to IFR % change for -8 ops/hr |
| 25 | -6% | -36% | 0% | 0% | -8% | -34% |
| 50 | -5% | -14% | 0% | 0% | -3% | -12% |
| 75 | -3% | -11% | 0% | 0% | -3% | -10% |
| 100 | -2% | 18% | 0% | 0% | -1% | 19% |
| 125 | -1% | -2% | 0% | 0% | -1% | -3% |
| 150 | 0% | 0% | 0% | 0% | 0% | 0% |
| 175 | 1% | 4% | 0% | 0% | 1% | 4% |
| 225 | -2% | 3% | 0% | 0% | -1% | 4% |
| 250 | 1% | 1% | 0% | 0% | 1% | 1% |
| 275 | 0% | -16% | 0% | 0% | 0% | -11% |
| 300 | 0% | -10% | 0% | 0% | 0% | -9% |
| 325 | 0% | 0% | 0% | 0% | 0% | 0% |

The greatest effects from changes in capacity are found on the aircraft between 37 and 62 seats per operation.   A reduction of 8 operations per hour between MVFR and IFR capacity levels for these aircraft causes a reduction of 16% of the scheduled flights and passenger demand, a 6% increase in airfares, a 14% reduction in fuel burn, and a 12% reduction in available seat miles.

The next greatest effects from changes in capacity are found on the aircraft between 62 and 87 seats per operation.   A reduction of 8 operations per hour between MVFR and IFR capacity levels for these aircraft causes a reduction of 11% of the scheduled flights and passenger demand, a 1% increase in airfares, an 11% reduction in fuel burn, and a 10% reduction in available seat miles.

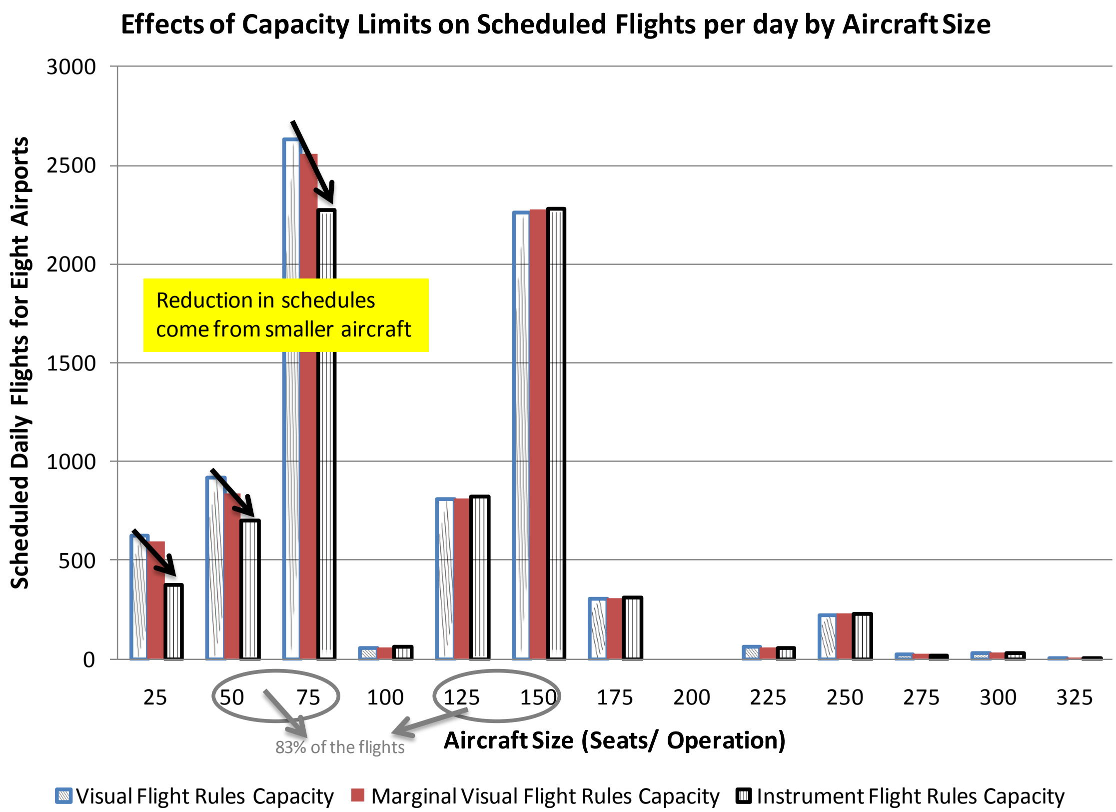



**Figure 52 Effects of capacity limits on scheduled flights per day by aircraft size**

Examining this reduction of flights by small aircraft in the schedule as runway capacity limits are reduced is shown in Figure 52. This figure clearly illustrates the reduction of daily flights in the schedule for aircraft between 12 and 87 seats per operation. Further examination of average profits per flight in Figure 53; show the flights removed from the schedule were the least profitable.

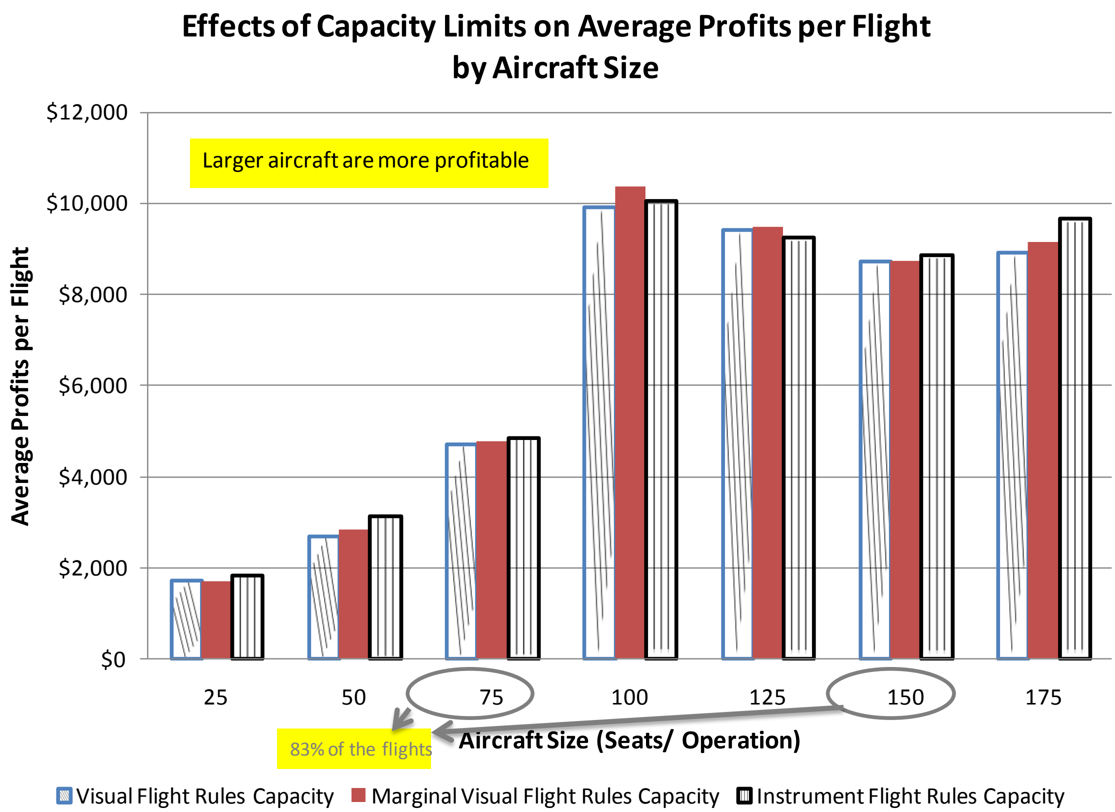



**Figure 53 Effects of capacity limits on average profits per flight by aircraft size**

## A.2 Impact of increased Fuel Prices on Airline Scheduling and Passenger Demand Behavior at VFR runway capacities

The effects of fuel price increases for the 595 markets which remain in the aggregated schedule for all scenarios are presented in this section. These markets are examined to evaluate effects from reducing runway capacity limits from $2 to $3, $3, to $4, and $4 to $5, with airport capacity limits fixed at VFR runway capacities. Increases in aviation fuel prices from $2 to $3 have more effect compared to increases in aviation fuel prices from $4 to $5, as shown in Figure 54.

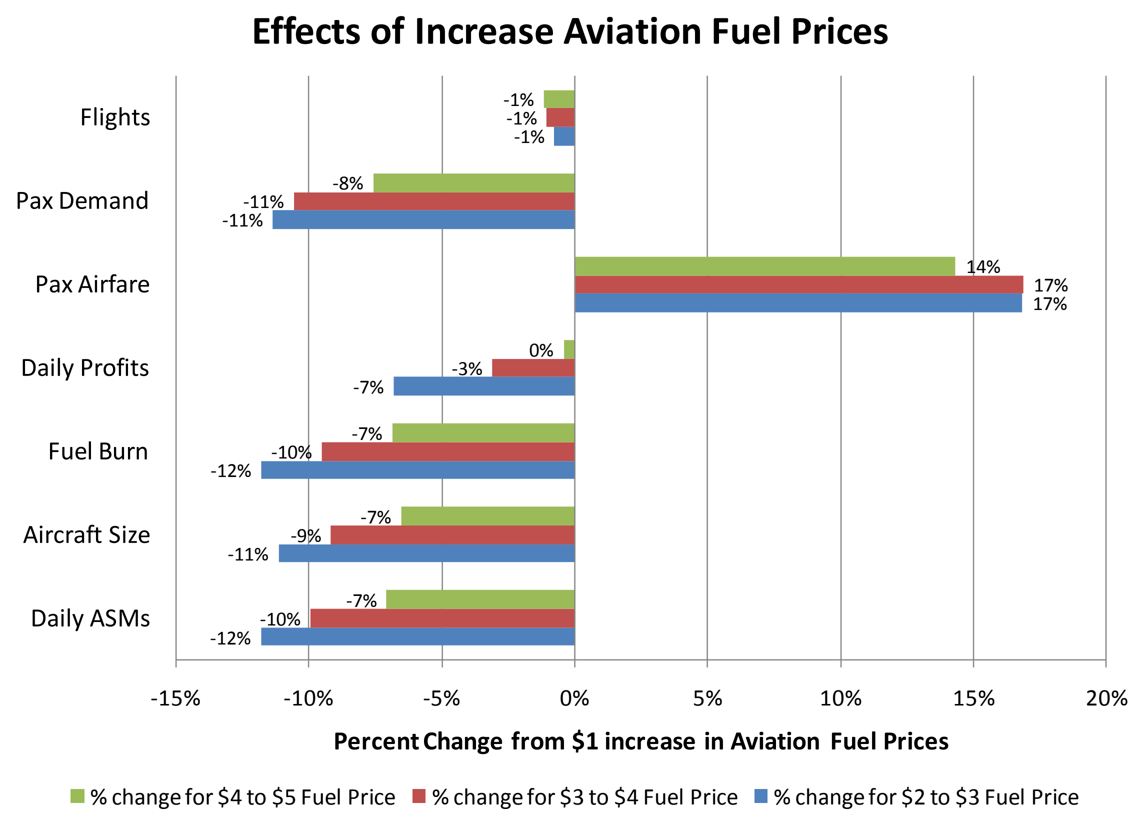



**Figure 54  Effects from increases in aviation fuel prices**

Increasing the aviation fuel prices from $2 to $3 in the ASOM triggers significant changes in almost all of the metrics examined. Frequency of service to markets is reduced by 1%, which is minor for a fuel price increase 50%. However, there are major changes in passenger demand (-11%), average airfare (+17%), daily airline profits (-7%), daily fuel burn (-12%), average aircraft size (-11%), and daily available seat miles (-12%). The increases in airfare are related with the decrease in passenger demand through the law of demand. The loss of this demand removes economic interaction between the markets and could possibly have very negative impacts on the leisure travel industry. Even with the increased airfares, this analysis shows the airlines will struggle to maintain profits. Since profits are dependent on the law of demand, the airlines cannot pass all of the increases in operational costs on to the passenger and expect to maintain daily profits. The reduction in the average aircraft size or seats per operation can be explained by the diseconomies of scale found in aircraft burn rates versus aircraft size, as discussed in chapter 3 of this dissertation. This down gauging of aircraft used in the schedule combined with minor changes in frequency of service to these markets causes the available seat miles provided by the schedule to get reduced, which puts the systems imbalance between supply and demand further out of balance. While reduced environmental impact from fuel burn is desirable, the overall domestic air transportation system suffers from increases in aviation fuel prices.

## Table 40 Airport analysis of the effects from aviation fuel price increases

| Capacity Limits (Ops per hour) | | | | Geographis Access | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model Inputs | | Historic | | Markets Served | | | | Flights per Day | | |
| Airports | VFR+ | 3QTR 2007 avg b/w 6am-10pm | Airports | VFR | MVFR | IFR | % change for $1 increase | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | 88 | 75 | BOS | Analysis for Markets in schedule at IFR capacity and $5 fuel price | | 56 | N/A | 1% | 0% | -1% |
| DFW | 168 | 134 | DFW | | | 115 | N/A | -1% | -2% | -2% |
| EWR | 88 | 79 | EWR | | | 70 | N/A | -2% | -1% | -1% |
| JFK | 88 | 81 | JFK | | | 47 | N/A | -1% | -4% | -2% |
| LGA | 88 | 77 | LGA | | | 57 | N/A | 0% | -1% | -1% |
| ORD | 160 | 180 | ORD | | | 121 | N/A | -1% | -1% | -1% |
| PHL | 96 | 87 | PHL | | | 76 | N/A | -1% | 0% | 0% |
| SFO | 96 | 65 | SFO | | | 53 | N/A | -3% | -1% | -2% |

| | Economic Access | | | | | | | Airline Profitability | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Passenger Demand | | | Average Airfare | | | | Daily Profits | | |
| Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | -12% | -11% | -9% | 19% | 17% | 16% | BOS | -5% | -2% | 1% |
| DFW | -14% | -8% | -8% | 21% | 13% | 14% | DFW | -7% | -3% | 0% |
| EWR | -12% | -9% | -7% | 19% | 16% | 15% | EWR | -5% | -3% | 1% |
| JFK | -11% | -11% | -6% | 16% | 17% | 12% | JFK | -10% | -7% | -5% |
| LGA | -10% | -8% | -5% | 16% | 15% | 12% | LGA | -3% | -1% | 2% |
| ORD | -9% | -15% | -8% | 13% | 22% | 15% | ORD | -7% | -3% | 0% |
| PHL | -12% | -10% | -6% | 17% | 17% | 14% | PHL | -7% | -3% | 0% |
| SFO | -12% | -10% | -10% | 16% | 16% | 16% | SFO | -9% | -6% | -3% |

| | Environmental Impact | | | | ATS Efficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | | | Average Aircraft Size | | | Daily ASMs | | |
| Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | -11% | -11% | -8% | BOS | -12% | -11% | -8% | -11% | -12% | -8% |
| DFW | -11% | -11% | -7% | DFW | -10% | -9% | -6% | -10% | -11% | -7% |
| EWR | -12% | -7% | -6% | EWR | -11% | -8% | -6% | -12% | -8% | -6% |
| JFK | -11% | -9% | -5% | JFK | -10% | -7% | -4% | -11% | -10% | -5% |
| LGA | -11% | -6% | -5% | LGA | -10% | -6% | -4% | -11% | -7% | -5% |
| ORD | -13% | -11% | -8% | ORD | -13% | -10% | -7% | -13% | -11% | -8% |
| PHL | -12% | -10% | -5% | PHL | -11% | -10% | -6% | -12% | -10% | -6% |
| SFO | -12% | -8% | -8% | SFO | -10% | -9% | -9% | -13% | -10% | -9% |

The effects of an aviation fuel price increase from $2 to $3 vary slightly across the airports examined, as shown in Table 40. Frequency of service to markets is reduced by 1% to 3%, with SFO showing the greatest reduction. Passenger demand is reduced by 9% to 14%, with DFW showing the greatest reduction and ORD showing the least reduction. Average airline airfares are increased by 13% to 21%, with DFW showing the greatest increase and ORD showing the smallest increase. Airline profits are reduced by 3% to 10%, with JFK showing the greatest reduction and LGA showing the least reduction in profits. Daily fuel burn from the schedule is reduced by 11% to 13%, with ORD showing the greatest reduction. Average seats per operation or aircraft size is reduced by 10% to 13%, with ORD showing the greatest reduction. Available seat miles in the schedule are reduced by 10% to 13%, with ORD and SFO showing the greatest reductions.

The results from evaluating the effects of increased fuel prices by market distance show the effects are relatively consistent regardless of the market distance as shown in Table 41. Since 79% of the flights are for markets from 125 to 1125 miles from the airport, this is where the analysis is focused. As shown in previous analysis in this section the effects are greater from increased fuel prices from $2 to $3, than they are from increases in fuel price from $3 to $4 or $4 to $5. These 428 markets from 125 to 1125 miles from the airports show consistent impacts from increased fuel prices for the four different 250 mile distance bands shown in Table 41. An increase of aviation fuel prices from $2 to $3 for these 428 markets results in a reduction of 1% of the scheduled flights, a reduction of 12% of the passengers served by the schedule, a 18% increase in airfares, a 5% reduction in profits, a 12% reduction in fuel burn, a 12% reduction in aircraft size, and a 12% reduction in available seat miles.

The 153 markets 1125 miles or more from the airports represent 20% of the flights in the airport schedules. An increase of aviation fuel prices from $2 to $3 for these 153 markets results in a reduction of 1% of the scheduled flights, a reduction of 10% of the passengers served by the schedule, a 17% increase in airfares, a 10% reduction in profits, a 11% reduction in fuel burn, a 7% reduction in aircraft size, and a 11% reduction in available seat miles.

## Table 41 Market distance analysis of the effects from increased aviation fuel prices

| Market Distance (miles) | Geographis Access: Markets Served VFR | MVFR | IFR | % change | Flights per Day: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Density of Flights (79%): % of VFR scheduled flights |
|---|---|---|---|---|---|---|---|---|
| <125 | Analysis for Markets in schedule at IFR capacity and $5 fuel price | | 14 | N/A | 0% | -1% | 5% | 2% |
| **125-375** | | | **138** | N/A | -1% | -1% | -1% | 28% |
| **375-625** | | | **110** | N/A | 0% | -1% | -2% | 19% |
| **625-875** | | | **106** | N/A | -1% | 0% | -1% | 19% |
| **875-1125** | | | **74** | N/A | -1% | -1% | -1% | 12% |
| 1125-1375 | | | 41 | N/A | -1% | 0% | -2% | 5% |
| 1375-1625 | | | 36 | N/A | 0% | -1% | -1% | 5% |
| 1625-1875 | | | 22 | N/A | 2% | -5% | -3% | 3% |
| 1875-2125 | | | 8 | N/A | 0% | -4% | 0% | 1% |
| 2125-2375 | | | 14 | N/A | -9% | -2% | -2% | 1% |
| 2375-2625 | | | 29 | N/A | -5% | -3% | -1% | 4% |
| >2625 | | | 3 | N/A | 7% | -7% | -14% | 0% |

| Market Distance (miles) | Economic Access – Passenger Demand: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Average Airfare: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Airline Profitability – Daily Profits: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
|---|---|---|---|---|---|---|---|---|---|
| <125 | -2% | -5% | -4% | 11% | 13% | 15% | -10% | -7% | -2% |
| **125-375** | -11% | -10% | -8% | 18% | 16% | 15% | -2% | 1% | 3% |
| **375-625** | -11% | -11% | -7% | 17% | 18% | 14% | -4% | -1% | 2% |
| **625-875** | -13% | -12% | -9% | 18% | 18% | 16% | -6% | -2% | 1% |
| **875-1125** | -12% | -9% | -8% | 17% | 16% | 15% | -7% | -3% | 0% |
| 1125-1375 | -13% | -8% | -8% | 19% | 15% | 14% | -8% | -4% | -1% |
| 1375-1625 | -7% | -9% | -5% | 14% | 16% | 13% | -7% | -4% | -2% |
| 1625-1875 | -6% | -18% | -7% | 10% | 24% | 14% | -11% | -6% | -3% |
| 1875-2125 | -5% | -11% | -5% | 14% | 16% | 12% | -13% | -12% | -9% |
| 2125-2375 | -13% | -9% | -5% | 17% | 14% | 13% | -17% | -14% | -11% |
| 2375-2625 | -15% | -7% | -3% | 19% | 13% | 10% | -10% | -8% | -6% |
| >2625 | -8% | -8% | -16% | 16% | 14% | 18% | -10% | -8% | -4% |

| Market Distance (miles) | Environmental Impact – Daily Fuel Burn: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | ATS Efficiency – Average Aircraft Size: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Daily ASMs: % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
|---|---|---|---|---|---|---|---|---|---|
| <125 | -2% | -5% | -1% | -2% | -4% | -8% | -2% | -5% | -4% |
| **125-375** | -12% | -10% | -7% | -11% | -8% | -7% | -12% | -10% | -8% |
| **375-625** | -12% | -11% | -8% | -12% | -10% | -6% | -12% | -11% | -8% |
| **625-875** | -14% | -11% | -9% | -13% | -11% | -8% | -14% | -11% | -9% |
| **875-1125** | -12% | -9% | -8% | -10% | -9% | -8% | -12% | -9% | -8% |
| 1125-1375 | -12% | -9% | -7% | -11% | -10% | -6% | -11% | -10% | -8% |
| 1375-1625 | -7% | -8% | -5% | -8% | -7% | -4% | -8% | -9% | -6% |
| 1625-1875 | -10% | -13% | -7% | -12% | -9% | -5% | -11% | -13% | -8% |
| 1875-2125 | -6% | -10% | -5% | -6% | -7% | -5% | -5% | -10% | -5% |
| 2125-2375 | -13% | -8% | -5% | -3% | -7% | -3% | -13% | -9% | -5% |
| 2375-2625 | -14% | -5% | -2% | -11% | -4% | -2% | -15% | -7% | -3% |
| >2625 | -5% | -8% | -15% | -14% | -2% | -2% | -8% | -8% | -16% |

The effects of increased fuel prices by aircraft size (average seats per operation) vary greatly as shown in Table 42. Since more than 83% of the flights are flown by aircraft between 37 to 87 seats per operation and between 112 to 162 seats per operation, this is where the analysis is focused.  As shown in previous analysis in this section the effects are greater from increased fuel prices from $2 to $3, than they are from increases in fuel price from $3 to $4 or $4 to $5.

The greatest effects from increases in fuel price are found on the aircraft between 137 and 162 seats per operation.   An increase of fuel prices from $2 to $3 for these aircraft cause a reduction of 23% of the scheduled flights, a reduction of 22% in passenger demand, a 18% increase in airfares, a 19% reduction in fuel burn, and a 18% reduction in available seat miles.

The next greatest effects from changes in capacity are found on the aircraft between 62 and 87 seats per operation.   An increase of fuel prices from $2 to $3 for these aircraft cause an increase of 20% of the scheduled flights, an increase of 22% in passenger demand, a 18% increase in airfares, a 25% increase in fuel burn, and a 27% increase in available seat miles.

This exchange of smaller aircraft for the aircraft between 137 and 162 seats per operation is explained by the diseconomies of scale discussed in chapter 3 of this dissertation.

# Table 42 Aircraft type/ class analysis of the effects from increased fuel prices

| Geographis Access | | | | | | | | Density of Flights |
|---|---|---|---|---|---|---|---|---|
| Markets Served | | | | Flights per Day | | | | 83% |
| VFR | MVFR | IFR | % change for $1 increase in Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % of VFR scheduled flights |
| Analysis for Markets in schedule at IFR capacity and $5 fuel price | | | N/A | 43% | 26% | 21% | 25 | 8% |
| | | | N/A | -1% | -2% | -4% | 50 | 12% |
| | | | N/A | 20% | 10% | 2% | 75 | 33% |
| | | | N/A | -23% | 48% | -15% | 100 | 1% |
| | | | N/A | -1% | 6% | 6% | 125 | 10% |
| | | | N/A | -23% | -32% | -27% | 150 | 28% |
| | | | N/A | -51% | -49% | -34% | 175 | 4% |
| | | | N/A | -16% | -12% | -26% | 225 | 1% |
| | | | N/A | -45% | -42% | -47% | 250 | 3% |
| | | | N/A | -46% | -43% | -75% | 275 | 0% |
| | | | N/A | -71% | -60% | -50% | 300 | 0% |
| | | | N/A | -100% | | | 325 | 0% |

| | Economic Access | | | | | | | Airline Profitability | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Passenger Demand | | | Average Airfare | | | | Daily Profits | | |
| Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| 25 | 44% | 25% | 21% | 18% | 10% | 11% | 25 | 62% | 31% | 31% |
| 50 | 0% | -2% | -4% | 18% | 19% | 18% | 50 | 5% | 6% | 6% |
| 75 | 20% | 11% | 2% | 18% | 14% | 13% | 75 | 32% | 19% | 11% |
| 100 | -23% | 49% | -14% | 13% | 55% | 16% | 100 | -28% | 89% | -23% |
| 125 | 0% | 6% | 6% | 19% | 14% | 12% | 125 | 1% | 5% | 4% |
| 150 | -22% | -32% | -27% | 18% | 16% | 13% | 150 | -21% | -30% | -25% |
| 175 | -52% | -48% | -35% | -4% | 20% | 17% | 175 | -65% | -45% | -39% |
| 225 | -14% | -14% | -26% | 13% | 23% | 20% | 225 | -19% | -11% | -22% |
| 250 | -44% | -43% | -47% | 3% | 11% | 17% | 250 | -53% | -47% | -45% |
| 275 | -43% | -46% | -75% | 0% | 21% | 72% | 275 | -52% | -49% | -47% |
| 300 | -70% | -61% | -50% | 9% | -27% | 38% | 300 | -70% | -87% | 8% |
| 325 | -100% | | | -100% | | | 325 | -100% | | |

| | Environmental Impact | | | | ATS Efficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | | | Average Aircraft Size | | | Daily ASMs | | |
| Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| 25 | 51% | 25% | 21% | 25 | No changes in aircraft size, these comparisons are made for same size aircraft | | | 54% | 23% | 21% |
| 50 | 3% | 4% | 0% | 50 | | | | 7% | 10% | 2% |
| 75 | 25% | 13% | 4% | 75 | | | | 27% | 14% | 4% |
| 100 | -18% | 119% | -5% | 100 | | | | -16% | 130% | -4% |
| 125 | 8% | 9% | 7% | 125 | | | | 11% | 10% | 8% |
| 150 | -19% | -31% | -26% | 150 | | | | -18% | -30% | -26% |
| 175 | -57% | -46% | -30% | 175 | | | | -58% | -47% | -29% |
| 225 | -12% | -4% | -20% | 225 | | | | -13% | -3% | -18% |
| 250 | -49% | -44% | -45% | 250 | | | | -50% | -44% | -44% |
| 275 | -51% | -40% | -67% | 275 | | | | -52% | -38% | -63% |
| 300 | -73% | -69% | -50% | 300 | | | | -72% | -69% | -50% |
| 325 | -100% | | | 325 | | | | -100% | | |

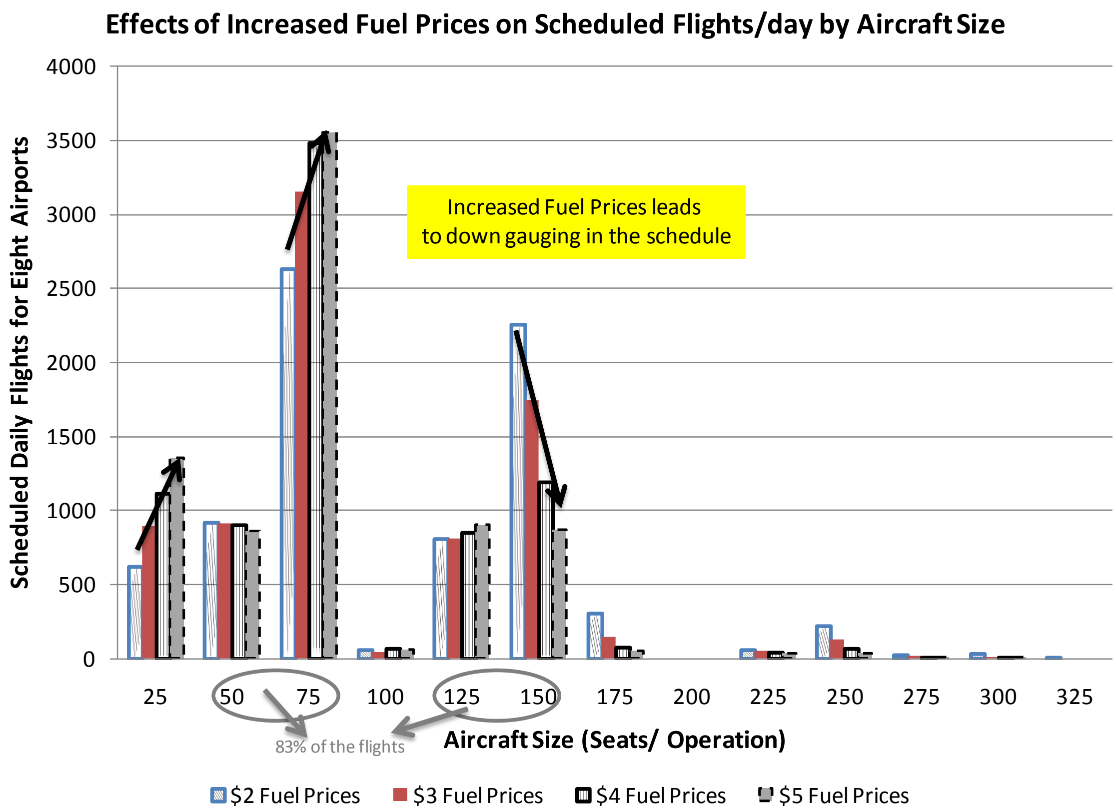



**Figure 55 Effects of Increased fuel prices on scheduled flights per day by aircraft size**

Further examination of this shift from 137 to 162 seat aircraft to 62 to 87 seat aircraft is illustrated in Figure 55. This analysis also shows an increase utilization of 13 to 37 seat aircraft as fuel prices are increased.

An examination of average profits per flight in Figure 56, show the flights from 137 to 162 seat aircraft that remain in the schedule at higher fuel prices are retaining their profitability. This is accomplished by removing the less profitable flights flown from 137 to 162 seat aircraft and replacing them with profitable flights flown by 62 to 87 seat aircraft. This results in the average profits for flights flown between 62 to 87 seat aircraft to increase.

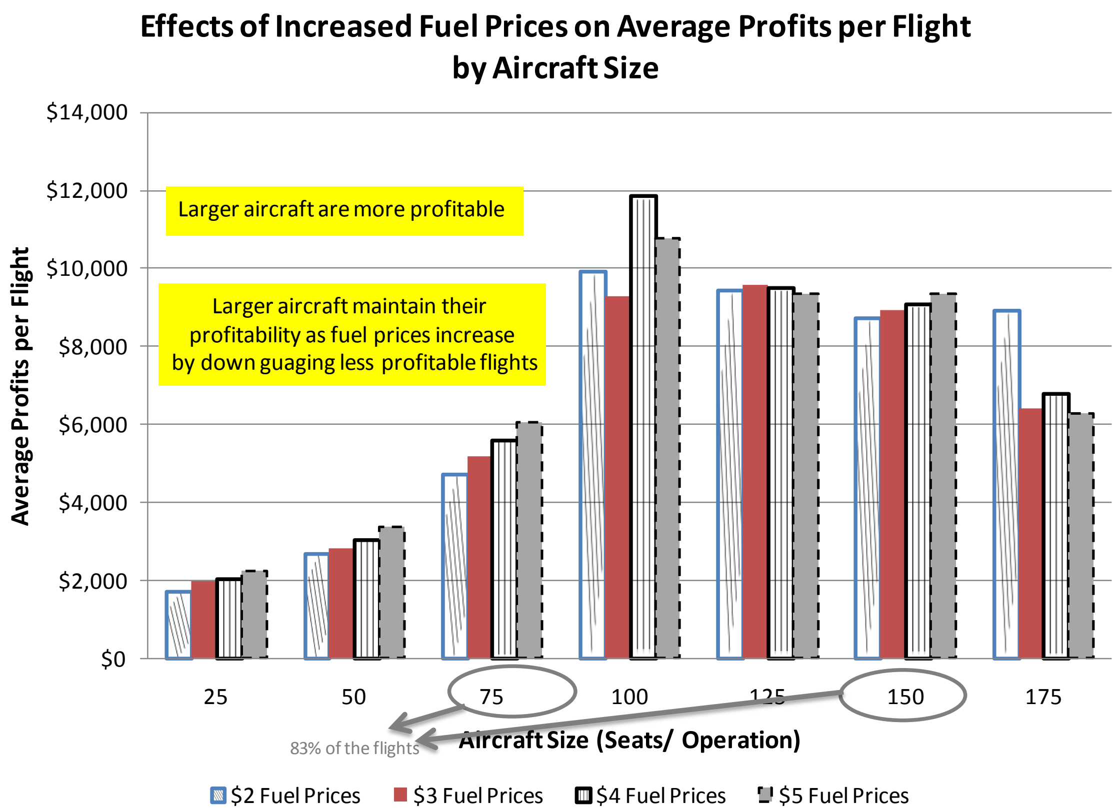



**Figure 56 Effects of increased fuel prices on average profits per flight by aircraft size**

Next the effects of fuel price increase from $2 to $5 for all eight airports by aircraft size are examined in Table 43. This analysis shows most airport schedules reduce the use of flights from 137 to 162 seat aircraft and increase the use of 62 to 87 seat and 12 to 37 seat aircraft in the schedules at $5 fuel prices.   The VFR schedule for LGA removes 112 to 137 seat and 162 to 187 seat aircraft from the schedule and replace these flights with 62 to 87 seat and 12 to 37 seat aircraft in the schedule when fuel prices are raised from $2 to $5.  The VFR schedule for SFO removes 137 to 162 seat and 237 to 262 seat aircraft from the schedule and replace these flights with 62 to 87 seat, 12 to 37 seat, and 112 to 137 seat aircraft in the schedule when fuel prices are raised from $2 to $5.

**Table 43 Percent change in scheduled flights for VFR runway capacity limits when fuel prices are increased from $2/ gallon to $5/ gallon, examined by aircraft size and airport.**

| Aircraft size (seats per operation) | % Change in scheduled flights when fuel prices increased from $2 per gallon to $5 per gallon | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **BOS** | **DFW** | **EWR** | **JFK** | **LGA** | **ORD** | **PHL** | **SFO** |
| **25** | **12%** | 3% | **19%** | 4% | **5%** | **12%** | **8%** | **9%** |
| **50** | 1% | | **-6%** | 1% | 1% | 1% | -1% | -1% |
| **75** | **17%** | **23%** | **5%** | **14%** | **8%** | **17%** | **21%** | 4% |
| **100** | | | -2% | 2% | | | | 1% |
| **125** | -3% | 1% | **11%** | -4% | **-6%** | -2% | 4% | **9%** |
| **150** | **-19%** | **-24%** | **-23%** | **-19%** | -3% | **-19%** | **-28%** | **-18%** |
| **175** | **-5%** | -2% | -4% | **-5%** | **-8%** | -2% | **-6%** | -1% |
| **200** | Not modeled in the ASOM due to lack of data in BTS for aircraft in this class | | | | | | | |
| **225** | | | | -1% | | -1% | -1% | |
| **250** | -2% | -3% | | | -1% | -4% | | **-8%** |
| **275** | | -1% | | | | -1% | | |
| **300** | | | | | | -1% | | -1% |

The next section will examine the effects of fuel price increases for schedules at IFR capacity limits.

## A.3 Impact of increased Fuel Prices on Airline Scheduling and Passenger Demand Behavior at IFR runway capacities

The effects of fuel price increases for the 595 markets which remain in the aggregated schedule for all scenarios are presented in this section. These markets are examined to evaluate effects from reducing runway capacity limits from $2 to $3, $3, to $4, and $4 to $5, with airport capacity limits fixed at IFR runway capacities. Increases in aviation fuel prices from $2 to $3 have more effect compared to increases in aviation fuel prices from $4 to $5, as shown in Figure 57.

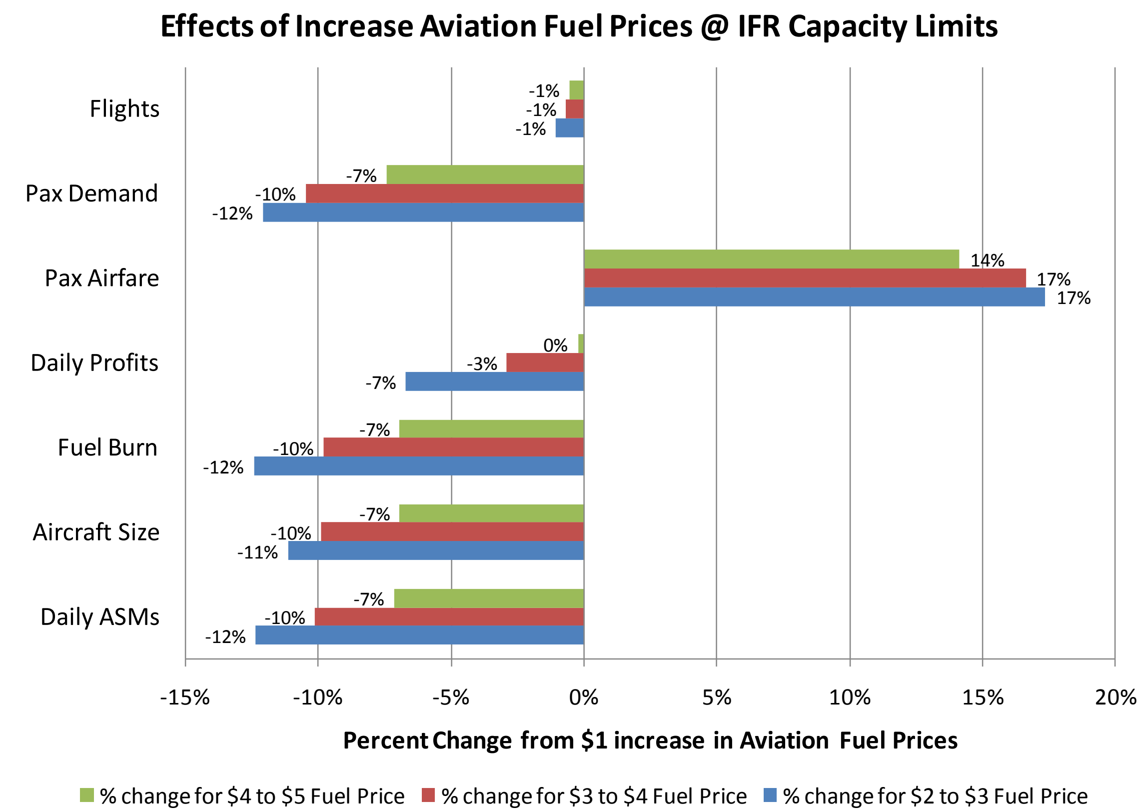



**Figure 57 Effects from increases in aviation fuel prices for schedules at IFR capacity limits**

Increasing the aviation fuel prices from $2 to $3 in the ASOM triggers significant changes in almost all of the metrics examined. Frequency of service to markets is reduced by 1%, which is minor for a fuel price increase 50%. However, there are major changes in passenger demand (-12%), average airfare (+17%), daily airline profits (-7%), daily fuel burn (-12%), average aircraft size (-11%), and daily available seat miles (-12%). The increases in airfare are related with the decrease in passenger demand through the law of demand. The loss of this demand removes economic interaction between the markets and could possibly have very negative impacts on the leisure travel industry. Even with the increased airfares, this analysis shows the airlines will struggle to maintain profits. Since profits are dependent on the law of demand, the airlines cannot pass all of the increases in operational costs on to the passenger and expect to maintain daily profits. The reduction in the average aircraft size or seats per operation can be explained by the diseconomies of scale found in aircraft burn rates versus aircraft size, as discussed in chapter 3 of this dissertation. This down gauging of aircraft used in the schedule combined with minor changes in frequency of service to these markets causes the available seat miles provided by the schedule to get reduced, which puts the systems imbalance between supply and demand further out of balance. While reduced environmental impact from fuel burn is desirable, the overall domestic air transportation system suffers from increases in aviation fuel prices.

**Table 44 Airport analysis of the effects from aviation fuel price increases for airport schedules at IFR capacities**

| Capacity Limits (Ops per hour) | | | | Geographis Access | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model Inputs | | | | Markets Served | | | | Flights per Day | | |
| Airports | IFR | Historic 3QTR 2007 avg b/w 6am-10pm | Airports | VFR | MVFR | IFR | % change for $1 increase in Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | 48 | 75 | BOS | Analysis for Markets in schedule at IFR capacity and $5 fuel price | | 56 | **N/A** | **0%** | **-1%** | **1%** |
| DFW | 104 | 134 | DFW | | | 115 | **N/A** | **-1%** | **0%** | **0%** |
| EWR | 64 | 79 | EWR | | | 70 | **N/A** | **0%** | **-1%** | **-1%** |
| JFK | 64 | 81 | JFK | | | 47 | **N/A** | **-3%** | **-3%** | **-2%** |
| LGA | 72 | 77 | LGA | | | 57 | **N/A** | **0%** | **-1%** | **-1%** |
| ORD | 128 | 180 | ORD | | | 121 | **N/A** | **0%** | **0%** | **0%** |
| PHL | 72 | 87 | PHL | | | 76 | **N/A** | **-1%** | **0%** | **0%** |
| SFO | 72 | 65 | SFO | | | 53 | **N/A** | **-3%** | **-1%** | **-2%** |

| | Economic Access | | | | | | | Airline Profitability | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Passenger Demand | | | Average Airfare | | | | Daily Profits | | |
| Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | **-10%** | **-13%** | **-9%** | **16%** | **19%** | **16%** | BOS | **-5%** | **-2%** | **1%** |
| DFW | **-12%** | **-11%** | **-6%** | **18%** | **16%** | **13%** | DFW | **-6%** | **-2%** | **0%** |
| EWR | **-12%** | **-8%** | **-8%** | **19%** | **15%** | **15%** | EWR | **-5%** | **-3%** | **1%** |
| JFK | **-12%** | **-9%** | **-6%** | **16%** | **16%** | **12%** | JFK | **-10%** | **-6%** | **-5%** |
| LGA | **-10%** | **-8%** | **-5%** | **16%** | **15%** | **12%** | LGA | **-3%** | **-1%** | **2%** |
| ORD | **-13%** | **-12%** | **-8%** | **18%** | **17%** | **15%** | ORD | **-7%** | **-2%** | **0%** |
| PHL | **-14%** | **-11%** | **-7%** | **18%** | **17%** | **15%** | PHL | **-7%** | **-3%** | **0%** |
| SFO | **-12%** | **-10%** | **-10%** | **17%** | **16%** | **16%** | SFO | **-9%** | **-6%** | **-3%** |

| | Environmental Impact | | | | ATS Efficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | | | Average Aircraft Size | | | Daily ASMs | | |
| Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Airports | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| BOS | **-11%** | **-12%** | **-8%** | BOS | **-9%** | **-12%** | **-10%** | **-11%** | **-13%** | **-7%** |
| DFW | **-12%** | **-12%** | **-6%** | DFW | **-11%** | **-10%** | **-6%** | **-12%** | **-11%** | **-6%** |
| EWR | **-12%** | **-7%** | **-7%** | EWR | **-12%** | **-7%** | **-7%** | **-12%** | **-7%** | **-7%** |
| JFK | **-13%** | **-8%** | **-6%** | JFK | **-9%** | **-7%** | **-4%** | **-13%** | **-9%** | **-6%** |
| LGA | **-11%** | **-6%** | **-5%** | LGA | **-10%** | **-6%** | **-4%** | **-11%** | **-7%** | **-5%** |
| ORD | **-14%** | **-11%** | **-8%** | ORD | **-13%** | **-12%** | **-8%** | **-13%** | **-12%** | **-8%** |
| PHL | **-14%** | **-11%** | **-6%** | PHL | **-12%** | **-11%** | **-7%** | **-13%** | **-10%** | **-6%** |
| SFO | **-12%** | **-8%** | **-8%** | SFO | **-10%** | **-9%** | **-9%** | **-13%** | **-9%** | **-9%** |

The effects of an aviation fuel price increase from $2 to $3 vary slightly across the airports examined, as shown in Table 44. Frequency of service to markets is reduced by 1% to 3%, with SFO and JFK showing the greatest reductions. Passenger demand is reduced by 10% to 14%, with PHL showing the greatest reduction and LGA showing the least reduction. Average airline airfares are increased by 16% to 19%, with EWR showing the greatest increase. Airline profits are reduced by 3% to 10%, with JFK showing the greatest reduction and LGA showing the least reduction in profits. Daily fuel burn from the schedule is reduced by 11% to 14%, with ORD and PHL showing the greatest reductions and BOS and LGA showing the least reductions. Average seats per operation or aircraft size is reduced by 9% to 13%, with ORD showing the greatest reduction and BOS and JFK showing the least reductions. Available seat miles in the schedule are reduced by 11% to 13%, with BOS and LGA showing the least reductions.

The results from evaluating the effects of increased fuel prices by market distance show the effects are relatively consistent regardless of the market distance as shown in Table 45. Since 78% of the flights are for markets from 125 to 1125 miles from the airport, this is where the analysis is focused. As shown in previous analysis in this section the effects are greater from increased fuel prices from $2 to $3, than they are from increases in fuel price from $3 to $4 or $4 to $5. These 428 markets from 125 to 1125 miles from the airports show consistent impacts from increased fuel prices for the four different 250 mile distance bands shown in Table 45. An increase of aviation fuel prices from $2 to $3 for these 428 markets results in a reduction of 1% of the scheduled flights, a reduction of 12% of the passengers served by the schedule, a 18% increase in airfares, a 5% reduction in profits, a 13% reduction in fuel burn, a 12% reduction in aircraft size, and a 12% reduction in available seat miles.

The 153 markets 1125 miles or more from the airports represent 20% of the flights in the airport schedules. An increase of aviation fuel prices from $2 to $3 for these 153 markets results in a reduction of 2% of the scheduled flights, a reduction of 8% of the passengers served by the schedule, a 17% increase in airfares, a 6% reduction in profits, a 8% reduction in fuel burn, a 7% reduction in aircraft size, and a 8% reduction in available seat miles.

## Table 45 Market Distance analysis of the effects from increased aviation fuel prices for schedules at IFR capacities

| | Geographis Access | | | | | | | | Density of Flights |
|---|---|---|---|---|---|---|---|---|---|
| | Markets Served | | | | Flights per Day | | | | 78% |
| Market Distance (miles) | VFR | MVFR | IFR | % change for $1 increase in Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Market Distance (miles) | % of IFR scheduled flights |
| <125 | Analysis for Markets in schedule at IFR capacity and $5 fuel price | | 14 | N/A | 6% | 2% | 0% | <125 | 1% |
| 125-375 | | | 138 | N/A | 0% | 0% | 1% | 125-375 | 26% |
| 375-625 | | | 110 | N/A | -1% | -1% | 0% | 375-625 | 20% |
| 625-875 | | | 106 | N/A | -1% | 0% | -1% | 625-875 | 20% |
| 875-1125 | | | 74 | N/A | -2% | 0% | 0% | 875-1125 | 12% |
| 1125-1375 | | | 41 | N/A | 1% | -2% | -2% | 1125-1375 | 5% |
| 1375-1625 | | | 36 | N/A | -2% | -1% | -2% | 1375-1625 | 6% |
| 1625-1875 | | | 22 | N/A | -1% | -3% | -2% | 1625-1875 | 3% |
| 1875-2125 | | | 8 | N/A | -8% | 0% | -4% | 1875-2125 | 1% |
| 2125-2375 | | | 14 | N/A | -10% | 0% | -7% | 2125-2375 | 1% |
| 2375-2625 | | | 29 | N/A | -7% | -1% | -1% | 2375-2625 | 4% |
| >2625 | | | 3 | N/A | 0% | -7% | -8% | >2625 | 0% |

| | Economic Access | | | | | | | Airline Profitability | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Passenger Demand | | | Average Airfare | | | | Daily Profits | | |
| Market Distance (miles) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Market Distance (miles) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| <125 | 3% | -1% | -7% | 10% | 13% | 14% | <125 | -5% | -1% | -2% |
| 125-375 | -10% | -10% | -7% | 17% | 16% | 15% | 125-375 | -1% | 1% | 4% |
| 375-625 | -13% | -11% | -7% | 19% | 17% | 14% | 375-625 | -4% | 0% | 2% |
| 625-875 | -14% | -13% | -9% | 19% | 18% | 15% | 625-875 | -6% | -2% | 2% |
| 875-1125 | -12% | -10% | -8% | 17% | 16% | 14% | 875-1125 | -7% | -3% | 0% |
| 1125-1375 | -11% | -12% | -7% | 17% | 17% | 14% | 1125-1375 | -8% | -4% | -1% |
| 1375-1625 | -10% | -8% | -7% | 16% | 15% | 13% | 1375-1625 | -7% | -4% | -2% |
| 1625-1875 | -11% | -13% | -6% | 16% | 17% | 13% | 1625-1875 | -11% | -6% | -3% |
| 1875-2125 | -8% | -6% | -9% | 14% | 14% | 13% | 1875-2125 | -14% | -12% | -10% |
| 2125-2375 | -11% | -9% | -9% | 15% | 15% | 14% | 2125-2375 | -18% | -14% | -12% |
| 2375-2625 | -16% | -5% | -3% | 19% | 13% | 10% | 2375-2625 | -10% | -8% | -7% |
| >2625 | -5% | -13% | -15% | 13% | 17% | 17% | >2625 | -10% | -8% | -4% |

| | Environmental Impact | | | | ATS Efficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | | | Average Aircraft Size | | | Daily ASMs | | |
| Market Distance (miles) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Market Distance (miles) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| <125 | 3% | -1% | -6% | <125 | -3% | -3% | -7% | 2% | -1% | -5% |
| 125-375 | -11% | -10% | -7% | 125-375 | -11% | -9% | -8% | -11% | -10% | -7% |
| 375-625 | -13% | -11% | -7% | 375-625 | -12% | -10% | -7% | -13% | -11% | -7% |
| 625-875 | -14% | -12% | -8% | 625-875 | -13% | -12% | -8% | -14% | -13% | -9% |
| 875-1125 | -13% | -10% | -8% | 875-1125 | -10% | -9% | -7% | -12% | -10% | -8% |
| 1125-1375 | -11% | -12% | -7% | 1125-1375 | -12% | -11% | -5% | -11% | -12% | -7% |
| 1375-1625 | -10% | -7% | -6% | 1375-1625 | -8% | -7% | -5% | -10% | -8% | -7% |
| 1625-1875 | -11% | -13% | -5% | 1625-1875 | -11% | -10% | -5% | -12% | -13% | -7% |
| 1875-2125 | -10% | -5% | -10% | 1875-2125 | 0% | -5% | -6% | -8% | -5% | -10% |
| 2125-2375 | -12% | -8% | -9% | 2125-2375 | -1% | -9% | -3% | -11% | -9% | -9% |
| 2375-2625 | -15% | -4% | -3% | 2375-2625 | -10% | -5% | -2% | -16% | -6% | -3% |
| >2625 | -4% | -11% | -13% | >2625 | -5% | -6% | -8% | -5% | -13% | -15% |

The effects of increased fuel prices by aircraft size (average seats per operation) for schedules at IFR capacity limits vary greatly as shown in Table 46. Since more than 85%

of the flights are flown by aircraft between 37 to 87 seats per operation and between 112 to 162 seats per operation, this is where the analysis is focused. As shown in previous analysis in this section the effects are greater from increased fuel prices from $2 to $3, than they are from increases in fuel price from $3 to $4 or $4 to $5.

The greatest effects from changes in capacity are found on the aircraft between 62 and 87 seats per operation. An increase of fuel prices from $2 to $3 for these aircraft cause an increase of 25% of the scheduled flights, an increase of 25% in passenger demand, a 18% increase in airfares, a 30% increase in fuel burn, and a 31% increase in available seat miles.

The next greatest effects from increases in fuel price are found on the aircraft between 137 and 162 seats per operation. An increase of fuel prices from $2 to $3 for these aircraft cause a reduction of 22% of the scheduled flights, a reduction of 21% in passenger demand, a 20% increase in airfares, a 18% reduction in fuel burn, and a 16% reduction in available seat miles.

This exchange of smaller aircraft for the aircraft between 137 and 162 seats per operation is explained by the diseconomies of scale discussed in chapter 3 of this dissertation.

## Table 46 Aircraft type/ class analysis of the effects from increased fuel prices for schedules at IFR capacities

| Geographis Access | | | | | | | | Density of Flights |
|---|---|---|---|---|---|---|---|---|
| Markets Served | | | | Flights per Day | | | | 85% |
| VFR | MVFR | IFR | % change for $1 increase in Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % of IFR scheduled flights |
| | | | N/A | 54% | 37% | 26% | 25 | 5% |
| | | | N/A | 1% | -1% | -1% | 50 | 10% |
| | | | N/A | 25% | 14% | 4% | 75 | 32% |
| | | | N/A | -29% | 32% | -3% | 100 | 1% |
| | | | N/A | -4% | 6% | 6% | 125 | 11% |
| Analysis for Markets in schedule at IFR capacity and $5 fuel price | | | N/A | -22% | -31% | -29% | 150 | 32% |
| | | | N/A | -51% | -54% | -25% | 175 | 4% |
| | | | N/A | -7% | -25% | -29% | 225 | 1% |
| | | | N/A | -48% | -42% | -44% | 250 | 3% |
| | | | N/A | -30% | -57% | -67% | 275 | 0% |
| | | | N/A | -73% | -50% | -50% | 300 | 0% |
| | | | N/A | -100% | | | 325 | 0% |

| | Economic Access | | | | | | | Airline Profitability | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Passenger Demand | | | Average Airfare | | | | Daily Profits | | |
| Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| 25 | 54% | 37% | 26% | 21% | 11% | 11% | 25 | 79% | 44% | 38% |
| 50 | 1% | -1% | -1% | 19% | 17% | 18% | 50 | 10% | 6% | 12% |
| 75 | 25% | 14% | 4% | 18% | 14% | 13% | 75 | 37% | 23% | 12% |
| 100 | -30% | 33% | -3% | 9% | 58% | 12% | 100 | -35% | 76% | -15% |
| 125 | -4% | 7% | 6% | 20% | 17% | 11% | 125 | 0% | 7% | 5% |
| 150 | -21% | -31% | -29% | 18% | 14% | 14% | 150 | -20% | -30% | -27% |
| 175 | -51% | -54% | -25% | -1% | 22% | 16% | 175 | -61% | -47% | -26% |
| 225 | -7% | -25% | -29% | 22% | 11% | 21% | 225 | -6% | -28% | -23% |
| 250 | -48% | -43% | -44% | 7% | 8% | 16% | 250 | -54% | -48% | -42% |
| 275 | -30% | -57% | -67% | -4% | 36% | 45% | 275 | -45% | -52% | -43% |
| 300 | -73% | -50% | -50% | 24% | -23% | 14% | 300 | -68% | -71% | -49% |
| 325 | -100% | | | -100% | | | 325 | -100% | | |

| | Environmental Impact | | | | ATS Efficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Daily Fuel Burn | | | | Average Aircraft Size | | | Daily ASMs | | |
| Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | Aircraft Size (seats) | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price | % change for $2 to $3 Fuel Price | % change for $3 to $4 Fuel Price | % change for $4 to $5 Fuel Price |
| 25 | 67% | 39% | 24% | 25 | | | | 68% | 39% | 23% |
| 50 | 3% | 3% | 4% | 50 | | | | 6% | 9% | 6% |
| 75 | 30% | 16% | 6% | 75 | | | | 31% | 17% | 6% |
| 100 | -30% | 96% | 3% | 100 | | | | -29% | 107% | 4% |
| 125 | 4% | 14% | 7% | 125 | No changes in aircraft size, these comparisons are made for same size aircraft | | | 7% | 16% | 7% |
| 150 | -18% | -30% | -27% | 150 | | | | -16% | -30% | -27% |
| 175 | -56% | -53% | -20% | 175 | | | | -56% | -53% | -20% |
| 225 | 5% | -26% | -22% | 225 | | | | 8% | -27% | -20% |
| 250 | -52% | -45% | -42% | 250 | | | | -52% | -45% | -42% |
| 275 | -41% | -47% | -62% | 275 | | | | -46% | -42% | -60% |
| 300 | -75% | -63% | -50% | 300 | | | | -74% | -64% | -50% |
| 325 | -100% | | | 325 | | | | -100% | | |

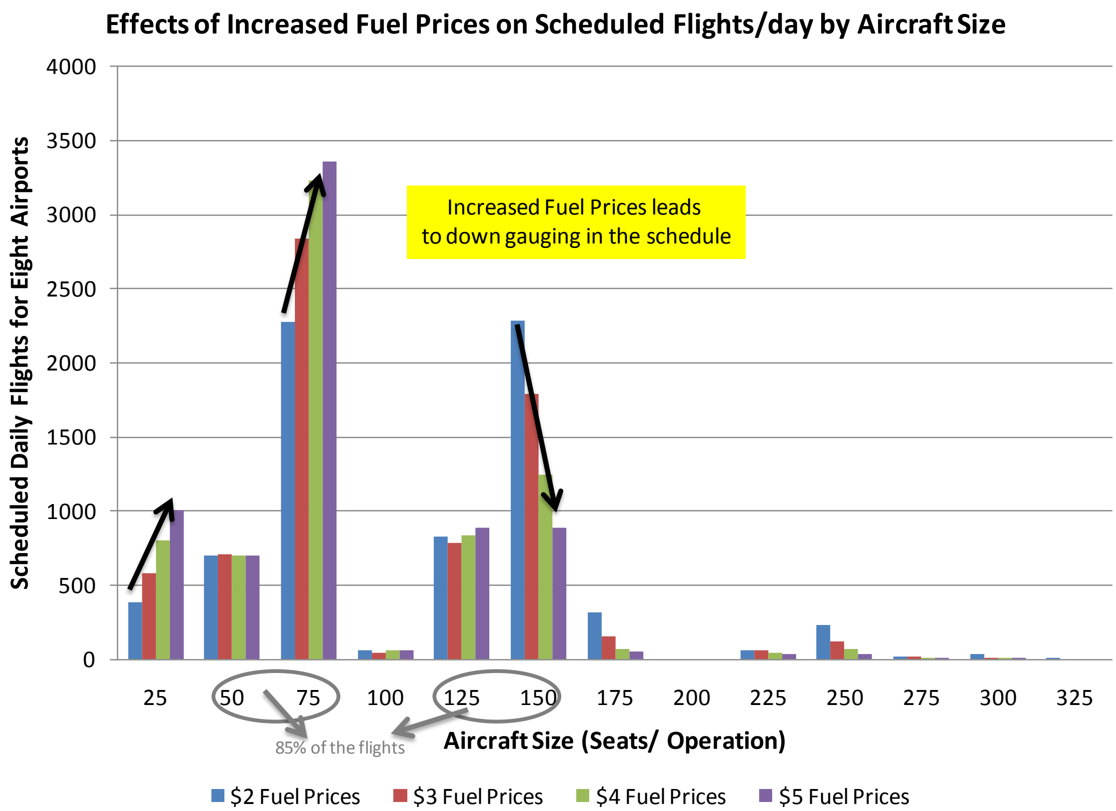



**Figure 58 Effects of increased fuel prices on IFR scheduled flights per day by aircraft size**

Further examination of this shift from 137 to 162 seat aircraft to 62 to 87 seat aircraft is illustrated in Figure 58. This analysis also shows an increase utilization of 13 to 37 seat aircraft as fuel prices are increased.

An examination of average profits per flight in Figure 59, show the flights from 137 to 162 seat aircraft that remain in the schedule at higher fuel prices are retaining their profitability. This is accomplished by removing the less profitable flights flown from 137 to 162 seat aircraft and replacing them with profitable flights flown by 62 to 87 seat aircraft. This results in the average profits for flights flown between 62 to 87 seat aircraft to increase.

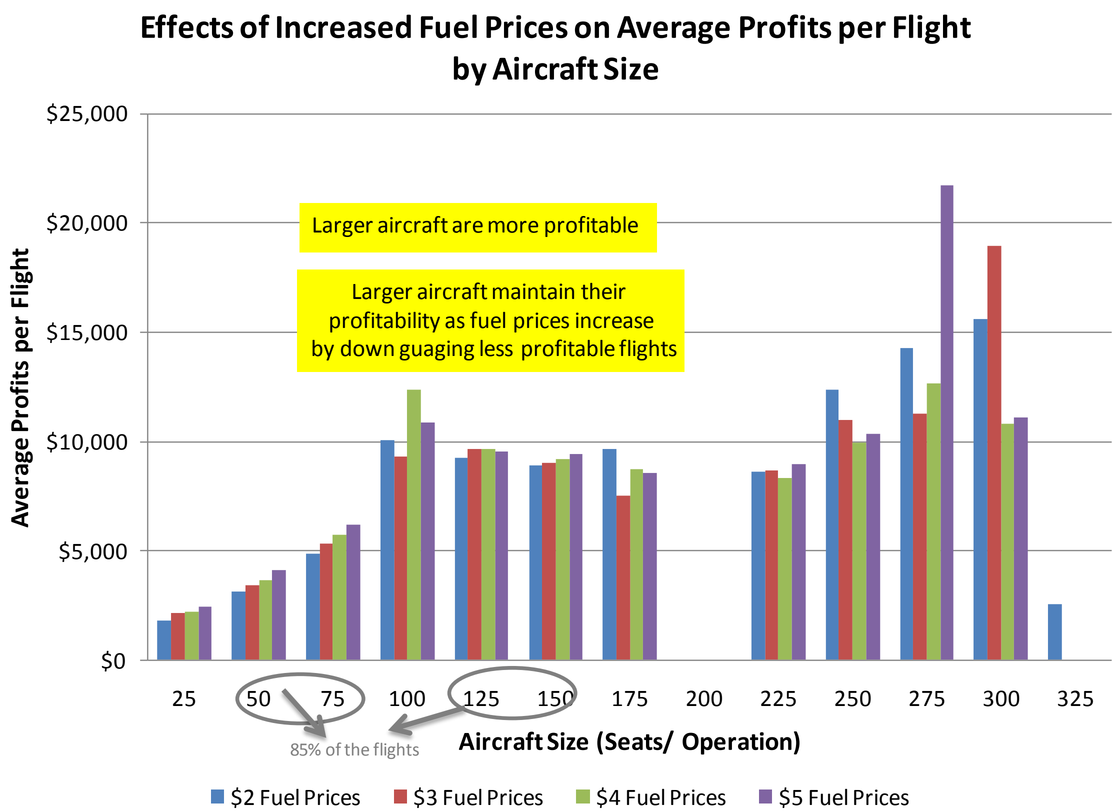



**Figure 59 Effects of increased fuel prices on average profits per flight by aircraft size**

Next the effects of fuel price increase from $2 to $5 for all eight airports by aircraft size are examined in Figure 59. This analysis shows most airport schedules reduce the use of flights from 137 to 162 seat aircraft and increase the use of 62 to 87 seat and 12 to 37 seat aircraft in the schedules at $5 fuel prices.   The IFR schedule for LGA removes 112 to 137 seat and 162 to 187 seat aircraft from the schedule and replace these flights with 62 to 87 seat and 12 to 37 seat aircraft in the schedule when fuel prices are raised from $2 to $5.  The IFR schedule for SFO removes 137 to 162 seat and 237 to 262 seat aircraft from the schedule and replace these flights with 62 to 87 seat, 12 to 37 seat, and 112 to 137 seat aircraft in the schedule when fuel prices are raised from $2 to $5.

**Table 47 Percent change in scheduled flights for VFR runway capacity limits when fuel prices are increased from $2/ gallon to $5/ gallon, examined by aircraft size and airport.**

| Aircraft size (seats per operation) | % Change in scheduled flights when fuel prices increased from $2 per gallon to $5 per gallon | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **BOS** | **DFW** | **EWR** | **JFK** | **LGA** | **ORD** | **PHL** | **SFO** |
| **25** | **12%** | 3% | **19%** | 4% | **5%** | **12%** | **8%** | **9%** |
| **50** | 1% | | **-6%** | 1% | 1% | 1% | -1% | -1% |
| **75** | **17%** | **23%** | **5%** | **14%** | **8%** | **17%** | **21%** | 4% |
| **100** | | | -2% | 2% | | | | 1% |
| **125** | -3% | 1% | **11%** | -4% | **-6%** | -2% | 4% | **9%** |
| **150** | **-19%** | **-24%** | **-23%** | **-19%** | -3% | **-19%** | **-28%** | **-18%** |
| **175** | **-5%** | -2% | -4% | **-5%** | **-8%** | -2% | **-6%** | -1% |
| **200** | Not modeled in the ASOM due to lack of data in BTS for aircraft in this class | | | | | | | |
| **225** | | | | -1% | | -1% | -1% | |
| **250** | -2% | -3% | | | -1% | -4% | | **-8%** |
| **275** | | -1% | | | | -1% | | |
| **300** | | | | | | -1% | | -1% |

The next section will examine the effects of fuel price increases and capacity limits on all eight airport schedules.

# APPENDIX B - ANALYSIS OF RUNWAY CAPACITY LIMITS AND INCREASED FUEL PRICES ON AIRLINE SCHEDULING AND PASSENGER DEMAND BEHAVIOR AT PHILADELPHIA INTERNATIONAL AIRPORT

Analysis of the ASOM schedule changes at Philadelphia International Airport as a function of runway capacity limits and fuel prices allows for a closer more detailed look at the decisions made within the ASOM model when the schedule is changed.

Table 48 shows how scenarios market service decays in the schedule as fuel prices are increased from $2 per gallon to $5 per gallon and as runway capacity limits are reduced from VFR to IFR levels of operation. This analysis shows under the most constrained schedule with $5 per gallon fuel prices and IFR runway capacity limits 4 markets (5%) lose service completely, 142 flights (15%) are removed, airfares are increased by $61 (63%), airline daily profits are reduced $586K (-13%), and the average seats per operation are reduced by 21 seats per operation (21%). Increased fuel prices caused the most impact on markets, average airfare, airline profits, and average aircraft size. Reduction of flights or service to markets was impacted most by reducing runway capacity limits.

**Table 48 Analysis of loss of service from the Philadelphia baseline schedule for 3rd QTR 2007 with $2 fuel prices and VFR runway capacity for all 12 scenarios**

| Philadelphia 3QTR 2007 | $2.00 | $3.00 | $4.00 | $5.00 |
|---|---|---|---|---|
| 96 ops/hr | **Baseline**<br>80 markets<br>962 flights<br>$97/ seat<br>$4.661M<br>100 seat/op | 0 markets<br>-10 flights<br>+$17/ seat<br>-$0.335M<br>-11 seat/op | -2 markets<br>-24 flights<br>+$37/ seat<br>-$0.461M<br>-20 seat/op | -3 markets<br>-30 flights<br>+$56/ seat<br>-$0.471M<br>-25 seat/op |
| 80 ops/hr | 0 markets<br>-66 flights<br>+$1/ seat<br>-$0.079M<br>+5 seat/op | -1 markets<br>-80 flights<br>+$18/ seat<br>-$0.409M<br>-7 seat/op | -3 markets<br>-90 flights<br>+$39/ seat<br>-$0.527M<br>-17 seat/op | -4 markets<br>-96 flights<br>+$59/ seat<br>-$0.528M<br>-22 seat/op |
| 72 ops/hr | -1 markets<br>-110 flights<br>+$2/ seat<br>-$0.155M<br>+8 seat/op | -1 markets<br>-122 flights<br>+$20/ seat<br>-$0.481M<br>-5 seat/op | -3 markets<br>-136 flights<br>+$41/ seat<br>-$0.592M<br>-15 seat/op | -4 markets<br>-142 flights<br>+$61/ seat<br>-$0.586M<br>-21 seat/op |

Table 49 shows scenarios market service is terminated in the schedule. These scenarios include the base scenario for Philadelphia scheduled with $2 fuel prices and VFR runway capacity constraints and the eleven more constrained schedules with higher fuel prices and lower runway capacity constraints. For the most constrained schedule at $4 fuel prices and IFR runway capacities service to Oakland, CA, New Haven, CT, LaGuardia, NY, and Erie, Pa are removed from the schedule.

**Table 49 Analysis of lost markets from Philadelphia scenarios**

| 3QTR 2007 | $2.00 | $3.00 | $4.00 | $5.00 |
|---|---|---|---|---|
| 96 ops/hr | **Baseline** 80 markets | No change | -OAK -LGA | -OAK - HVN - LGA |
| 80 ops/hr | No change | - ERI | - OAK - ERI - LGA | - OAK - ERI - HVN - LGA |
| 72 ops/hr | - ERI | - ERI | - OAK - ERI - LGA | - OAK - ERI - HVN - LGA |

OAK (Oakland, CA), HVN (New Haven, CT), LGA (New York, NY)
Dropped because unable to increase airfares to cover cost
ERI (Erie, PA) dropped because of Caps and Profitability

**Table 50 Summary of overall impact on Philadelphia schedules from increased fuel prices and reduced runway capacity limits. Yellow highlighted cells indicate significant impact.**

| | | Decrease in Runway Capacity 8 ops/ hr | $1 Increase in Fuel Price |
|---|---|---|---|
| Geographic Access | Markets | 0% | -1% |
| | Flights | -4% | -1% |
| Economic Access | Rev/ Seat | 1% | 20% |
| Airline Profitability | Daily Profit | -1% | -3% |
| Network Efficiency | Gauge | 2% | -9% |

Table 50 shows a summary of impact on all markets due to increased fuel prices and reduced runway capacity limits. While reductions in runway capacity show marginal impacts for these measures, an one dollar increase in fuel price show significant impacts for average airfare (+20%) and for average aircraft size (-9%).

While the loss of service to four markets out of eighty seems to be a lot, the analysis in Table 51 shows the loss of these markets has only marginal impact on the overall schedule. In fact, the changes in schedule are dominated by the changes in service to markets that remain in the schedule for all scenarios. Therefore, to provide a more accurate analysis of the impact of fuel prices and capacity limits on Philadelphia, only impacts on the 76 markets that are served in all scenarios are analyzed.

**Table 51 Impact of Fuel Price and Capacity constraints on the 3rd QTR 2007 schedule, by impact from dropped service versus reduced service to markets**

| PHL | Flights | Passenger Demand | Avg Airfare | Daily Profits | Fuel Burn | Aircraft Size | Daily ASMs |
|---|---|---|---|---|---|---|---|
| Impact from dropped Markets (4) | -2% | -2% | -1% | 0% | -1% | -1% | -1% |
| Impact from changes in kept Markets (76) | -12% | -31% | 63% | -12% | -29% | -21% | -28% |

Table 52 examines the impact of reducing Philadelphia's runway capacity limits from VFR to IFR at $2 fuel prices compared to the impact of increasing fuel prices from $2 to $5 while keeping Philadelphia's runway capacity limits at VFR levels. As analysis of all markets showed, reduction in runway capacity from VFR to IFR reduced flights and increased aircraft size marginally. While increasing fuel prices from $2 to $5 significantly reduced passengers served in the schedule, increased the airfares these passengers were charged, reduced fuel burn, reduced average seats per operation, reduced available seat miles in the schedule and reduced profits. However this increase in fuel prices did not reduce the service frequency or number of flights in the schedule.

**Table 52 Impact of Fuel Price and Capacity constraints on the 3rd QTR 2007 schedule, by impact from dropped service versus reduced service to markets**

| PHL | Flights | Passenger Demand | Avg Airfare | Daily Profits | Fuel Burn | Aircraft Size | Daily ASMs |
|---|---|---|---|---|---|---|---|
| VFR to IFR for kept Markets (76) @$2 | -11% | -5% | 1% | -3% | -3% | 7% | -2% |
| $2 to $5 for kept Markets (76) @VFR | -1% | -26% | 56% | -10% | -25% | -25% | -25% |

Table 52 examines the impact of reducing Philadelphia's runway capacity limits from VFR to IFR at $2 fuel prices compared to the impact of increasing fuel prices from $2 to $5 while keeping Philadelphia's runway capacity limits at VFR levels. As analysis of all markets showed, reduction in runway capacity from VFR to IFR reduced flights and increased aircraft size marginally. While increasing fuel prices from $2 to $5 significantly reduced passengers served in the schedule, increased the airfares these passengers were charged, reduced fuel burn, reduced average seats per operation, reduced available seat miles in the schedule and reduced profits. However this increase in fuel prices did not reduce the service frequency or number of flights in the schedule.

## B.1 Impact of reduced runway capacity limits at Philadelphia International Airport

In this section a closer examination of the impact of runway capacity limits on the schedule for Philadelphia will be provided. As runway capacity is reduced at Philadelphia more 150 seat aircraft and fewer 75 seat aircraft are chosen to serve the markets in the schedule, as shown in Figure 60.

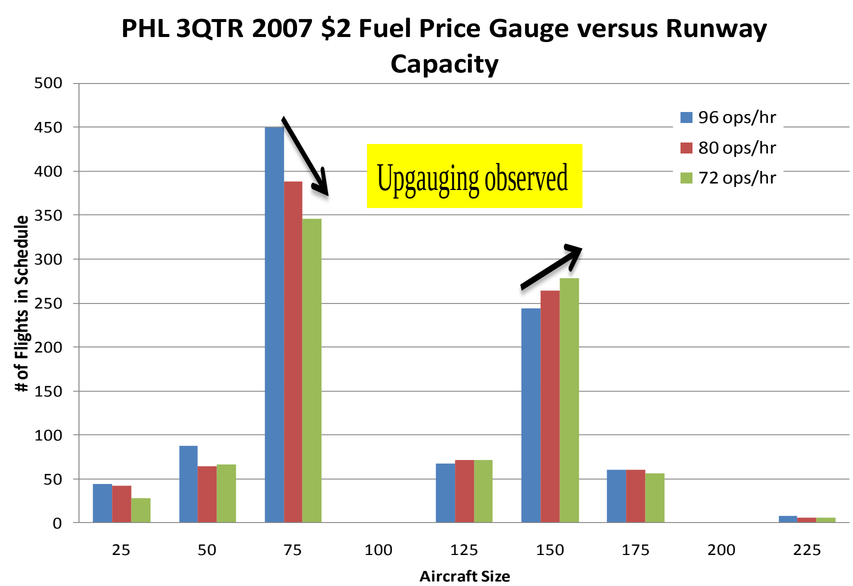



**Figure 60 Effect of runway capacity limits on aircraft size in the schedule for daily operations at Philadelphia International Airport 3QTR 2007**

This phenomenon can start to be explained by examining the profits per seat from the aircraft flown in the schedule, as shown in Figure 61. For all three capacity scenarios (VFR, MVFR, and IFR), the profits per seat for the 150 seat aircraft is approximately the same as the 75 seat aircraft. Therefore, the ASOM increases the aircraft size for some of the flights in the schedule constrained by reduced runway capacity limits.

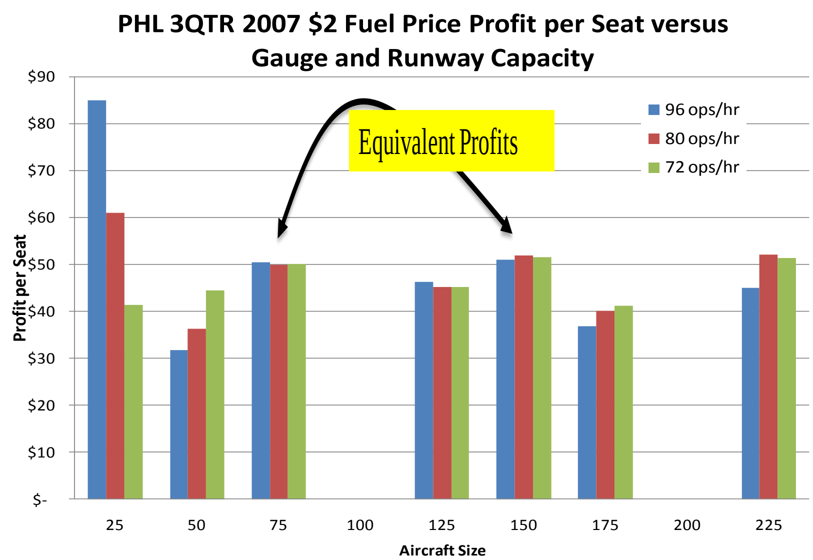



**Figure 61 Effect of runway capacity limits on profit per seat for different aircraft sizes for daily operations at Philadelphia International Airport 3QTR 2007**

The ASOM eliminates the least profitable round trip flights in the schedule where the constraints from reduced runway capacity limits exist, Table 53 and Table 54. In Table 53 for arrivals at Philadelphia at 7:45pm, service to Scranton, PA and Salisbury, MD is removed from the schedule when the runway capacity is reduced by 2 arrivals per 15 min (VFR to MVFR). And service to Rochester, NY is removed from the schedule when the runway capacity is reduced by 1 arrival per 15 min (MVFR to IFR). In Table 54 for arrivals at Philadelphia at 4:15pm, service to Binghamton, NY and Baltimore, MD is removed from the schedule when the runway capacity is reduced by 2 arrivals per 15 min (VFR to MVFR). And service to Harrisburg, PA is removed from the schedule when the runway capacity is reduced by 1 arrival per 15 min (MVFR to IFR). These examples show how the ASOM removes the lowest roundtrip flights from the schedule first, since the model seeks to maximize the profit from the schedule.

**Table 53 Minimum Roundtrip profits for flights arriving at Philadelphia International Airport at 7:45pm. Least profitable roundtrip markets are removed as runway capacity limits are reduced.**

| Roundtrip profits for markets arriving at 7:45pm for PHL | Airport Runway Capacity Levels (Arrivals/ 15 min) | | |
|---|---|---|---|
| | VFR (12) | MVFR (10) | IFR (9) |
| DEN | $21,912 | $21,919 | $14,459 |
| SJU | $15,854 | $15,854 | $17,971 |
| DTW | $10,975 | $10,814 | $10,369 |
| MKE | $10,942 | $11,125 | $10,736 |
| BUF | $6,114 | $4,429 | $5,077 |
| BOS | $1,123 | $9,854 | $11,274 |
| PVD | $5,639 | $6,175 | $6,175 |
| GSP | $5,252 | $5,252 | $5,252 |
| BDL | $3,474 | $5,220 | $5,220 |
| ROC | $2,799 | $2,794 | Dropped MVFR to IFR |
| SBY | $942 | Dropped VFR to MVFR | |
| AVP | $797 | | |

**Table 54 Minimum Roundtrip profits for flights arriving at Philadelphia International Airport at 4:15pm. Least profitable roundtrip markets are removed as runway capacity limits are reduced. 3 slots are reserved for international or cargo flights.**

| Roundtrip profits for markets arriving at 4:15pm for PHL | Airport Runway Capacity Levels (Arrivals/ 15 min) | | |
|---|---|---|---|
| | VFR (12) | MVFR (10) | IFR (9) |
| Reserved for International and Cargo Flights | | | |
| | | | |
| | | | |
| SFO | $29,737 | $30,964 | $29,842 |
| DTW | $12,963 | $11,666 | $11,216 |
| MCO | $7,198 | $6,795 | $7,077 |
| CVG | $4,308 | $7,005 | $6,855 |
| ORF | $4,874 | $4,921 | $6,167 |
| BTV | $4,329 | $4,445 | $4,445 |
| MDT | $1,416 | $1,416 | Dropped MVFR to IFR |
| BGM | $638 | Dropped VFR to MVFR | |
| BWI | $441 | | |

## B.2 Impact of increased fuel prices at Philadelphia International Airport

In this section a closer examination of the impact of increased fuel prices on the schedule for Philadelphia will be provided. As fuel prices are increased at Philadelphia more 75 seat aircraft and fewer 150 seat aircraft are chosen to serve the markets in the schedule, as shown in Figure 62.

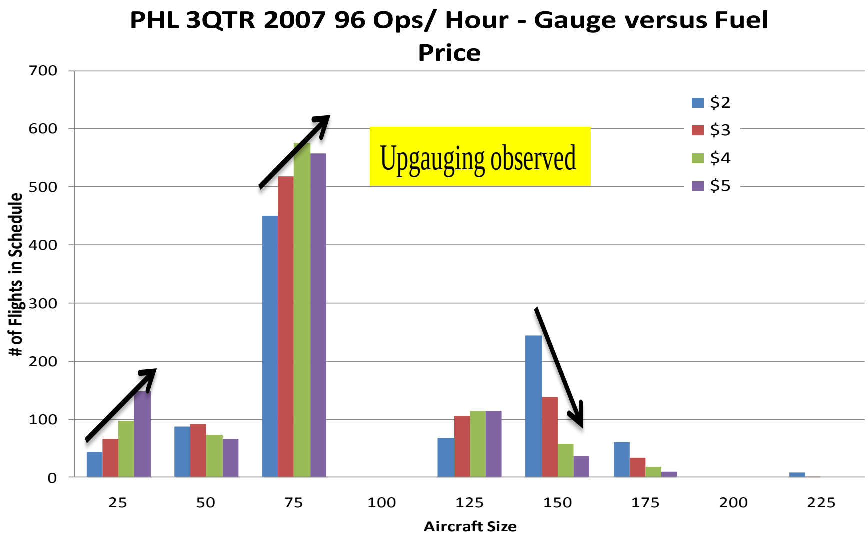



**Figure 62  Effect of increased fuel prices on aircraft size in the schedule for daily operations at Philadelphia International Airport 3QTR 2007**

This phenomenon can start to be explained by examining the profits per seat from the aircraft flown in the schedule, as shown in Figure 63.  For all four fuel price scenarios ($2, $3, $4, & $5), the profits per seat for the 150 seat aircraft is approximately the same as the 75 seat aircraft.

This analysis shows how the ASOM model swaps service from 150 aircraft to 75 seat aircraft for markets unable to offset the increased costs from fuel prices with airfare. Therefore, the ASOM chooses to serve fewer passengers at higher airfares to offset increased operational costs from higher fuel prices, minimize lost airline profits and maintain service to these markets.

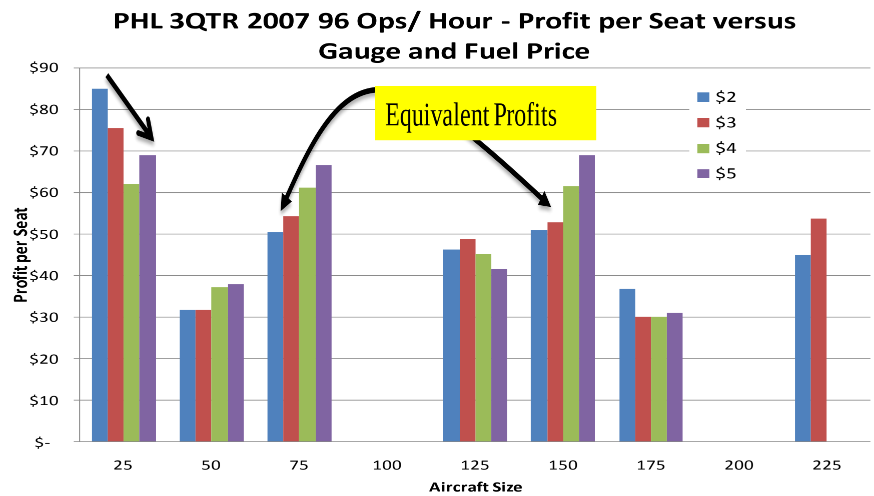



**Figure 63 Effect of increased fuel prices on profit per seat for different aircraft sizes for daily operations at Philadelphia International Airport 3QTR 2007**

Figure 64, Figure 65, and Figure 66 show the potential profits from different aircraft sizes to three different markets (Atlanta, Boston, and Dallas-Fort Worth) for different fuel prices. This analysis shows that increased fuel prices make the 75 seat aircraft the most profitable choice in the schedule for these markets but this transition occurs at different fuel prices. For flights from Philadelphia to Atlanta, the 75 seat aircraft becomes the most profitable choice for the ASOM between $2 and $3. For flights from Philadelphia to Boston and Dallas-Fort Worth, the 75 seat aircraft becomes the most profitable choice for the ASOM between $3 and $4.

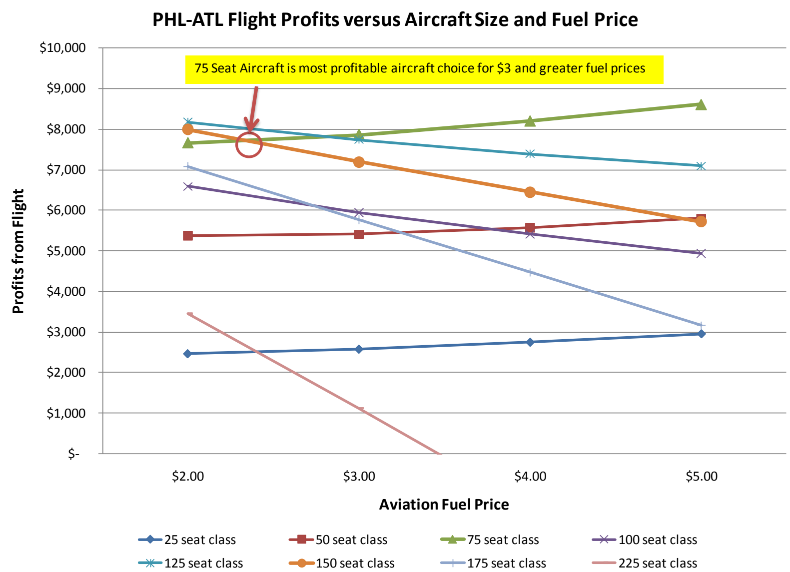



**Figure 64  One-way flight profits by aircraft size versus fuel price for service from Philadelphia to Atlanta**

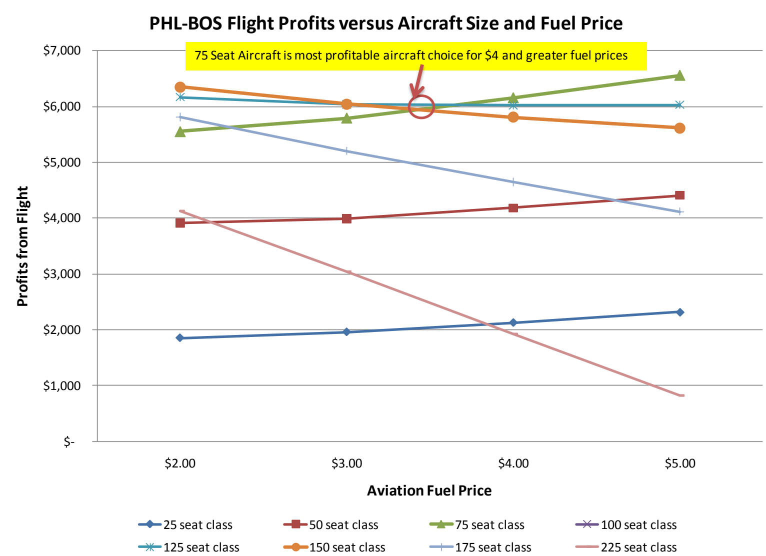



**Figure 65  One-way flight profits by aircraft size versus fuel price for service from Philadelphia to Boston**

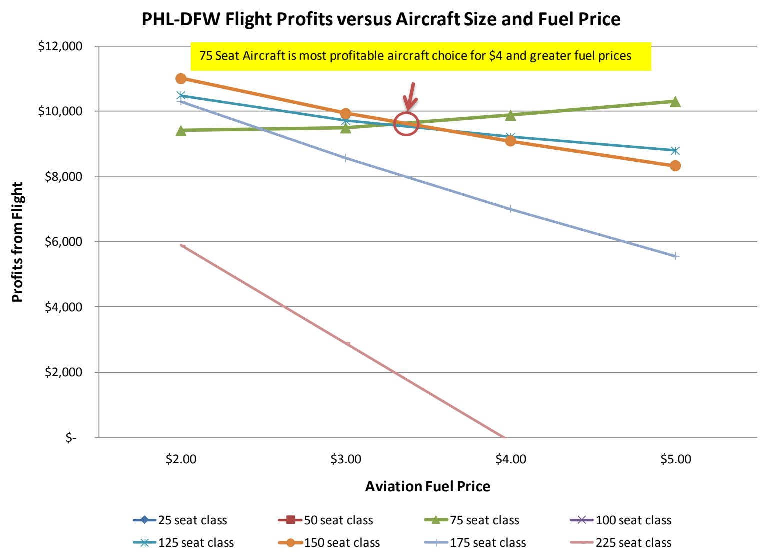



**Figure 66 One-way flight profits by aircraft size versus fuel price for service from Philadelphia to Dallas-Fort Worth**

# APPENDIX C - ANALYSIS OF THE EFFECTS OF FUEL PRICE ON MODERN AND BEST IN CLASS FLEETS

Aircraft direct operating costs, flights hours, and gallons of fuel issued for flights operations reported by the airlines for different aircraft types are found in the BTS P52 database. (U.S. DOT/BTS 2010) This data is combined with the average aircraft sizes as reported in the BTS T100 database, to evaluate aircraft costs by seat classes of aircraft as shown in Table 55.

This data is aggregated by seat class as shown in Table 20 to provide aircraft direct operating costs by hour and average fuel burn rates by aircraft class for a current aircraft scenario, for a modern aircraft smoothed scenario, and for a best in class (BIC) scenario as shown below in Table 56. Note current reporting aircraft are absent for the 200 and 350 seat classes.

## Table 55 BTS P52 reported costs, flight hours and gallons issued 3QTR 2002 – 4QTR2010

| Aircraft Name | Air Fuel Issued | Total Air Hours | Total Flights $ | Total Fuel $ | Avg Seats |
|---|---|---|---|---|---|
| **⊟25** | **573,289** | **2,772** | **2,658,584** | **947,504** | **31** |
| British Aerospace Jetstream 41 | 33,486 | 185 | 171,115 | 47,609 | 30 |
| Dassault-Breguet Mystere-Falcon | 2,404 | 6 | 14,256 | 9,186 | 15 |
| Dehavilland Dhc8-100 Dash-8 | 45,871 | 224 | 229,236 | 117,181 | 37 |
| Dehavilland Dhc8-200q Dash-8 | 78,240 | 329 | 384,947 | 126,905 | 37 |
| Dornier 328 | 1,957 | 10 | 11,526 | 2,088 | 32 |
| Dornier 328 Jet | 65,247 | 148 | 151,197 | 61,217 | 32 |
| Embraer Emb-120 Brasilia | 176,007 | 1,016 | 930,287 | 359,298 | 30 |
| Saab-Fairchild 340/B | 170,076 | 854 | 766,020 | 224,019 | 34 |
| **⊟50** | **8,589,935** | **19,019** | **26,082,814** | **12,719,710** | **48** |
| Aerospatiale/Aeritalia Atr-42 | 9,136 | 36 | 55,477 | 9,283 | 46 |
| Canadair Rj-100/Rj-100er | 361,640 | 738 | 1,335,160 | 706,772 | 50 |
| Canadair Rj-200er /Rj-440 | 4,060,526 | 9,247 | 14,160,263 | 6,840,976 | 50 |
| Embraer-135 | 477,870 | 958 | 1,240,001 | 718,827 | 38 |
| Embraer-140 | 539,028 | 1,128 | 1,481,180 | 1,072,785 | 44 |
| Embraer-145 | 3,139,725 | 6,909 | 7,807,876 | 3,369,431 | 50 |
| Fokker F28-4000/6000 Fellowship | 2,009 | 2 | 2,857 | 1,636 | 60 |
| **⊟75** | **3,036,901** | **6,623** | **10,125,148** | **5,463,319** | **77** |
| Aerospatiale/Aeritalia Atr-72 | 170,344 | 663 | 1,137,018 | 338,904 | 65 |
| Avroliner Rj85 | 13,783 | 25 | 22,109 | 14 | 87 |
| British Aerospace Bae-146-300 | 78,351 | 92 | 215,788 | 99,378 | 87 |
| Canadair Crj 900 | 597,190 | 1,004 | 1,770,299 | 1,167,686 | 83 |
| Canadair Rj-700 | 1,683,596 | 3,467 | 5,477,380 | 3,163,834 | 68 |
| Dehavilland Dhc8-400 Dash-8 | 200,530 | 524 | 833,386 | 413,604 | 75 |
| Embraer 170 | 228,303 | 732 | 570,970 | 232,515 | 71 |
| Embraer Erj-175 | 64,805 | 117 | 98,198 | 47,384 | 78 |
| **⊟100** | **2,278,738** | **2,402** | **6,629,253** | **3,841,721** | **99** |
| Boeing 727-100 | 89,455 | 74 | 459,196 | 137,200 | 94 |
| Embraer 190 | 439,638 | 606 | 1,601,305 | 971,057 | 100 |
| Fokker 100 | 180,704 | 219 | 416,299 | 151,980 | 100 |
| Mcdonnell Douglas Dc9 Super 87 | 47,186 | 46 | 127,370 | 105,502 | 109 |
| Mcdonnell Douglas Dc-9-10 | 31,215 | 32 | 79,878 | 28,731 | 90 |
| Mcdonnell Douglas Dc-9-15f | 15,112 | 20 | 61,434 | 39,174 | 90 |
| Mcdonnell Douglas Dc-9-30 | 1,231,420 | 1,187 | 3,117,222 | 1,932,425 | 100 |
| Mcdonnell Douglas Dc-9-40 | 244,007 | 219 | 766,548 | 475,652 | 110 |
| **⊟125** | **27,251,996** | **32,338** | **81,309,055** | **47,046,877** | **123** |
| Airbus Industrie A-318 | 172,903 | 196 | 488,438 | 338,213 | 114 |
| Airbus Industrie A319 | 5,965,815 | 7,344 | 19,479,204 | 11,318,197 | 127 |
| Boeing 717-200 | 2,100,535 | 2,517 | 7,367,710 | 3,818,645 | 114 |
| Boeing 737-100/200 | 631,074 | 640 | 1,537,184 | 733,807 | 127 |
| Boeing 737-200c | 125,265 | 117 | 309,217 | 183,635 | 117 |
| Boeing 737-300 | 7,583,485 | 8,762 | 21,227,271 | 11,754,430 | 133 |
| Boeing 737-500 | 2,035,251 | 2,357 | 6,189,121 | 3,441,500 | 115 |
| Boeing 737-700/700lr | 8,033,821 | 9,908 | 23,099,102 | 14,313,398 | 136 |
| Mcdonnell Douglas Dc-8-40 | 3,468 | 2 | 9,673 | 778 | 124 |
| Mcdonnell Douglas Dc-9-50 | 600,379 | 496 | 1,602,135 | 1,144,273 | 125 |
| **⊟150** | **31,099,769** | **31,319** | **94,530,296** | **57,253,928** | **145** |
| Airbus Industrie A320-100/200 | 8,783,805 | 10,032 | 26,972,610 | 16,743,104 | 150 |
| Boeing 727-200/231a | 1,213,988 | 807 | 4,257,409 | 1,897,688 | 141 |
| Boeing 737-400 | 1,703,311 | 1,937 | 5,494,007 | 3,022,761 | 138 |
| Boeing 737-800 | 7,106,670 | 7,700 | 23,304,509 | 13,583,303 | 153 |
| Mcdonnell Douglas Dc9 Super 80/Md8 | 11,978,567 | 10,524 | 33,566,245 | 21,399,313 | 140 |
| Mcdonnell Douglas Md-90 | 313,427 | 319 | 935,517 | 607,758 | 150 |
| **⊟175** | **21,098,940** | **17,559** | **60,980,358** | **38,819,204** | **178** |
| Airbus Industrie A321 | 1,060,516 | 1,073 | 2,842,536 | 1,936,927 | 185 |
| Boeing 737-900 | 811,003 | 849 | 2,352,272 | 1,561,211 | 170 |
| Boeing 757-200 | 16,694,830 | 14,008 | 49,377,616 | 31,022,288 | 183 |
| Boeing 767-200/Er/Em | 2,517,373 | 1,620 | 6,349,241 | 4,260,922 | 171 |
| Mcdonnell Douglas Dc-8-61 | 3,474 | 2 | 14,555 | 7,071 | 180 |
| Mcdonnell Douglas Dc-8-72 | 11,744 | 8 | 44,137 | 30,786 | 180 |
| **⊟225** | **2,828,276** | **1,779** | **9,172,708** | **5,102,516** | **220** |
| Airbus Industrie A310-200c/F | 767,805 | 430 | 2,991,040 | 1,315,032 | 220 |
| Boeing 757-300 | 1,316,069 | 957 | 3,668,839 | 2,586,814 | 221 |
| Mcdonnell Douglas Dc-8-62 | 97,033 | 51 | 254,572 | 177,533 | 220 |
| Mcdonnell Douglas Dc-8-63f | 59,298 | 26 | 198,211 | 123,187 | 220 |
| Mcdonnell Douglas Dc-8-71 | 225,865 | 122 | 952,129 | 455,518 | 220 |
| Mcdonnell Douglas Dc-8-73 | 275,093 | 145 | 733,155 | 269,277 | 220 |
| Mcdonnell Douglas Dc-8-73f | 87,114 | 49 | 374,761 | 175,155 | 220 |
| **⊟250** | **11,872,878** | **7,169** | **34,830,244** | **22,871,327** | **248** |
| Airbus Industrie A300b/C/F-100/200 | 35,624 | 16 | 52,574 | 2,613 | 250 |
| Airbus Industrie A300-B2 | 287 | 0 | 1,990 | 732 | 250 |
| Boeing 767-300/300er | 11,775,727 | 7,131 | 34,602,080 | 22,764,069 | 239 |
| Lockheed L-1011-1/100/200 | 41,635 | 15 | 102,809 | 51,515 | 250 |
| Mcdonnell Douglas Dc-10-40 | 19,606 | 7 | 70,793 | 52,398 | 250 |
| **⊟275** | **7,311,708** | **3,614** | **22,302,795** | **13,783,256** | **272** |
| Airbus Industrie A300-600/R/Cf/Rcf | 2,938,942 | 1,554 | 11,174,746 | 5,465,594 | 267 |
| Boeing 767-400/Er | 2,313,675 | 1,243 | 5,973,817 | 4,604,816 | 268 |
| Lockheed L-1011-500 Tristar | 124,771 | 48 | 321,600 | 197,891 | 283 |
| Mcdonnell Douglas Dc-10-10 | 1,796,053 | 720 | 4,412,822 | 3,172,961 | 270 |
| Mcdonnell Douglas Dc-10-30cf | 138,266 | 50 | 419,810 | 341,994 | 270 |
| **⊟300** | **14,816,058** | **6,492** | **38,539,572** | **27,737,666** | **297** |
| Airbus A330-300 | 188,104 | 94 | 477,224 | 415,195 | 298 |
| Airbus Industrie A330-200 | 2,018,098 | 1,023 | 5,668,276 | 4,254,746 | 297 |
| Boeing 777-200/200lr/233lr | 10,143,473 | 4,478 | 26,442,390 | 19,446,111 | 289 |
| Mcdonnell Douglas Dc-10-30 | 2,466,383 | 897 | 5,951,682 | 3,621,614 | 304 |
| **⊟325** | **5,858,319** | **2,264** | **19,207,908** | **10,144,588** | **323** |
| Mcdonnell Douglas Md-11 | 5,858,319 | 2,264 | 19,207,908 | 10,144,588 | 323 |
| **⊟375** | **7,696,316** | **2,248** | **18,252,934** | **12,401,841** | **363** |
| Boeing 747-400 | 7,696,316 | 2,248 | 18,252,934 | 12,401,841 | 363 |
| **⊟400** | **1,280,344** | **344** | **2,963,303** | **2,059,435** | **400** |
| Boeing 747c | 28,366 | 10 | 121,403 | 65,763 | 400 |
| Boeing 747f | 1,251,978 | 335 | 2,841,900 | 1,993,672 | 400 |
| **⊟425** | **3,772,962** | **1,007** | **7,151,433** | **4,482,485** | **430** |
| Boeing 747-200/300 | 3,772,962 | 1,007 | 7,151,433 | 4,482,485 | 430 |
| **⊟450** | **791,882** | **202** | **1,586,896** | **1,201,277** | **452** |
| Boeing 747-100 | 791,882 | 202 | 1,586,896 | 1,201,277 | 452 |

The hourly air fuel consumption is calculated by dividing total air fuels issued for the aggregate aircraft class by the total air hours flown by the same seat class.

The hourly aircraft direct expenses not related to fuel consumption are calculated by subtracting total fuel costs from total direct operational costs for the aggregate aircraft class, then dividing this by the total air hours flown by the same seat class. These operational costs varied based upon the aircraft type.

**Table 56 ASOM cost factors and burn Rates aggregated by aircraft sizes for current, modern, and best in class scenarios**

| | Current as Reported in BTS | | Modern Smoothed | | BIC Smoothed | |
|---|---|---|---|---|---|---|
| Size | Gallons/ Hr | Avg $/ hr - fuel | Gallons/ Hr | Avg $/ hr - fuel | Gallons/ Hr | Avg $/ hr - fuel |
| 25 | 206 | $ 616 | 164 | $ 320 | 139 | $ 340 |
| 50 | 452 | $ 703 | 334 | $ 618 | 283 | $ 634 |
| 75 | 459 | $ 704 | 511 | $ 893 | 433 | $ 882 |
| 100 | 942 | $ 1,058 | 695 | $ 1,145 | 589 | $ 1,084 |
| 125 | 843 | $ 1,059 | 885 | $ 1,374 | 750 | $ 1,239 |
| 150 | 979 | $ 1,144 | 1082 | $ 1,580 | 918 | $ 1,348 |
| 175 | 1201 | $ 1,262 | 1286 | $ 1,763 | 1091 | $ 1,411 |
| 200 | **no historic data reported** | | 1497 | $ 1,923 | 1270 | $ 1,428 |
| 225 | 1589 | $ 2,287 | 1715 | $ 2,061 | 1454 | $ 1,398 |
| 250 | 1651 | $ 1,660 | 1939 | $ 2,175 | 1644 | $ 1,322 |
| 275 | 2023 | $ 2,357 | 2170 | $ 2,267 | 1840 | $ 1,200 |
| 300 | 2282 | $ 1,664 | 2408 | $ 2,336 | 2042 | $ 1,200 |
| 325 | 2588 | $ 4,004 | 2652 | $ 2,382 | 2250 | $ 1,200 |
| 350 | **no historic data reported** | | 2907 | $ 2,393 | 2466 | $ 1,200 |
| 375 | 3424 | $ 2,603 | 3162 | $ 2,405 | 2682 | $ 1,200 |
| 400 | 3741 | $ 2,535 | 3426 | $ 2,382 | 2907 | $ 1,200 |
| 425 | 3748 | $ 2,651 | 3698 | $ 2,337 | 3138 | $ 1,200 |
| 450 | 3927 | $ 1,912 | 3976 | $ 2,268 | 3374 | $ 1,200 |

The current aircraft reported in the BTS P52 database, shown in Figure 67; do not reveal smooth curves when plotting direct operation costs minus fuel and aviation fuel burn rates per seat. This was an important observation of the input data for the ASOM model since the model will be maximizing profit by subtracting direct costs from revenue. Early runs of the ASOM model showed the model did not like to choose the 50 or 100 seat classes in the schedules, where historically these sized aircraft are flown. Since the burn rates for these classes are much higher than their neighboring seat classes these flight options were typically avoided. These cost factors and burn rates are used in the current aircraft scenarios. The ASOM does not force an airline to use its current fleet but rather allows it to up gauge or down gauge to more efficient aircraft. This is both a limitation and a capability of the model. The model instructs the aviation industry what economic advantages exist for aircraft purchases, without the higher capital costs considered.

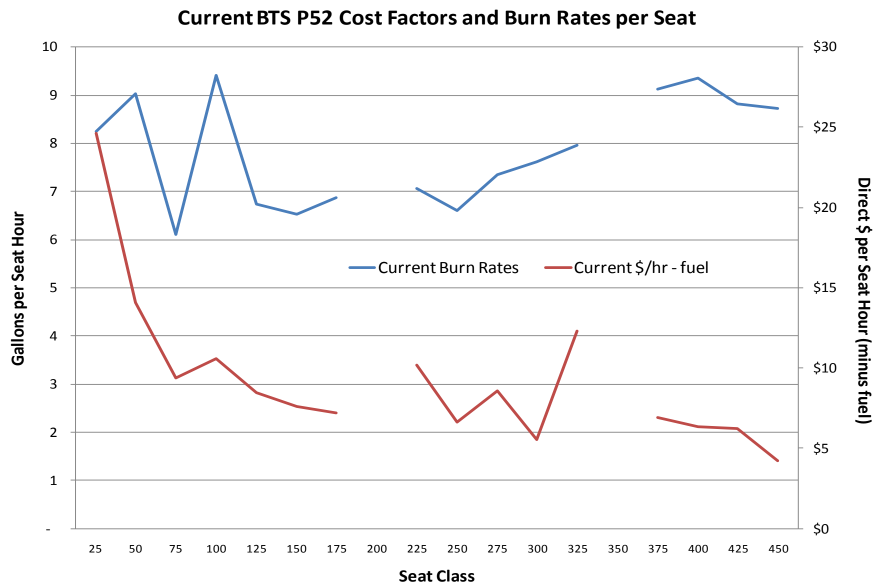



**Figure 67 Current BTS P52 cost factors and burn rates per seat**

To develop a modern aviation cost and performance scenario, all aircraft with higher burn rates per seat than 10 gallons per seat-hour were removed and regressions were performed to derive new cost factors and burn rates for a modern fleet of aircraft. Putting all the aircraft on the same regression line of costs per seat-hour and gallons per seat-hour, removes any biases of the ASOM choosing an aircraft type over another because of lags which exist in the air transportation fleet modernization programs. These new formulas also allow cost factors and burn rates to be assigned to the 200 and 250 seat classes. The formulas are as follows:

Gallons/ Seat-Hour = 0.0054 x seats + 6.4057, with an $R^2$ of 0.4065

Direct $ / Seat-Hour = -0.0183 x seats + 13.276, with an $R^2$ of 0.4722

Note even when eliminating the older less efficient aircraft from this analysis there are no economies of scale observed for aircraft burn rates per seat versus aircraft size.

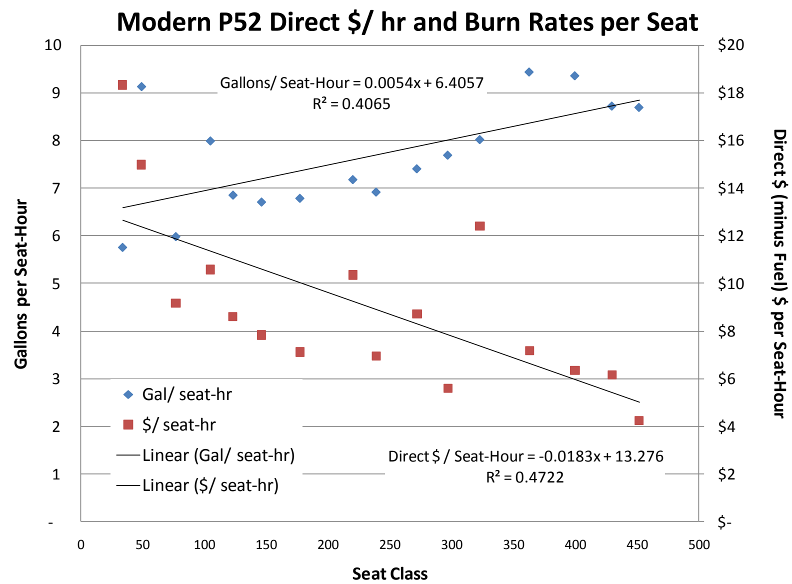



**Figure 68 Modern aircraft scenario direct cost factors and burn rates per seat, with regression formulas**

To develop a best in class aviation cost and performance scenario, the following aircraft in Table 56 were regressed for cost factors and burn rates per seat as shown in Figure 68.

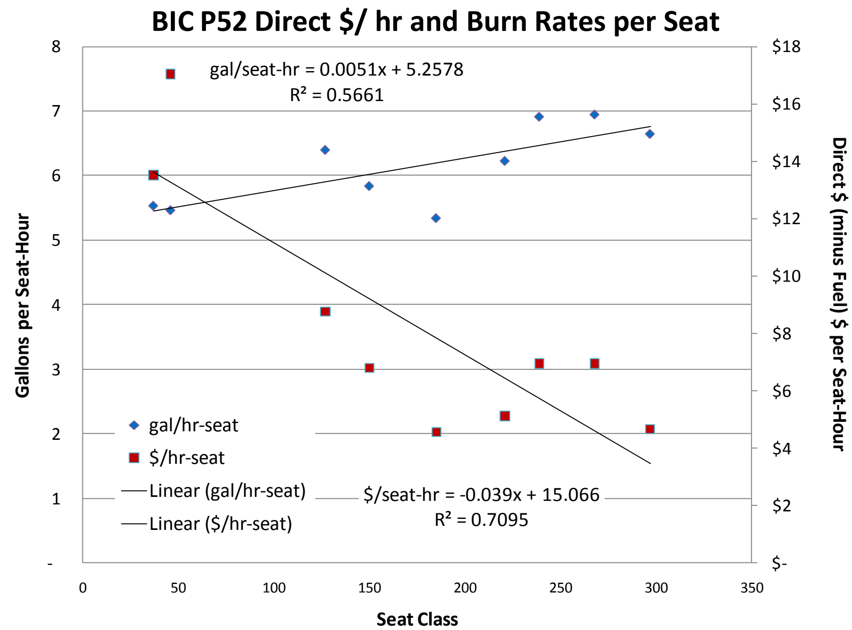



**Figure 69 Best in class aircraft scenario direct cost factors and burn rates per seat, with regression formulas**

Putting all the aircraft on the same regression line of costs per seat-hour and gallons per seat-hour, removes any biases of the ASOM choosing an aircraft type over another because of lags which exist in the air transportation fleet modernization programs. These new formulas also allow cost factors and burn rates to be assigned to the 200 and 250 seat classes. The formulas are as follows:

Gallons/ Seat-Hour = 0.0051 x seats + 5.2578, with an $R^2$ of 0.5661

Direct $ / Seat-Hour = - 0.039 x seats + 15.066, with an $R^2$ of 0.7095

Note even with best in class aircraft from this analysis there are no economies of scale observed for aircraft burn rates per seat versus aircraft size.

**Table 57 Best in class aircraft from BTS P52 database**

| Name | Seats | gal/hr-seat | $/hr-seat |
|---|---|---|---|
| Dehavilland Dhc8-100 Dash-8 | 37 | 5.53 | $ 13.52 |
| Aerospatiale/Aeritalia Atr-42 | 46 | 5.46 | $ 17.03 |
| Airbus Industrie A319 | 127 | 6.40 | $ 8.75 |
| Airbus Industrie A320-100/200 | 150 | 5.84 | $ 6.80 |
| Airbus Industrie A321 | 185 | 5.34 | $ 4.56 |
| Boeing 757-300 | 221 | 6.23 | $ 5.12 |
| Boeing 767-300/300er | 239 | 6.91 | $ 6.95 |
| Boeing 767-400/Er | 268 | 6.94 | $ 6.95 |
| Airbus Industrie A330-200 | 297 | 6.64 | $ 4.65 |

For the best in class scenario the direct cost minus fuel went negative for the larger aircraft sizes so these costs were frozen at $1200 per hour as previously shown in Table 57 and graphically shown below in Figure 70.

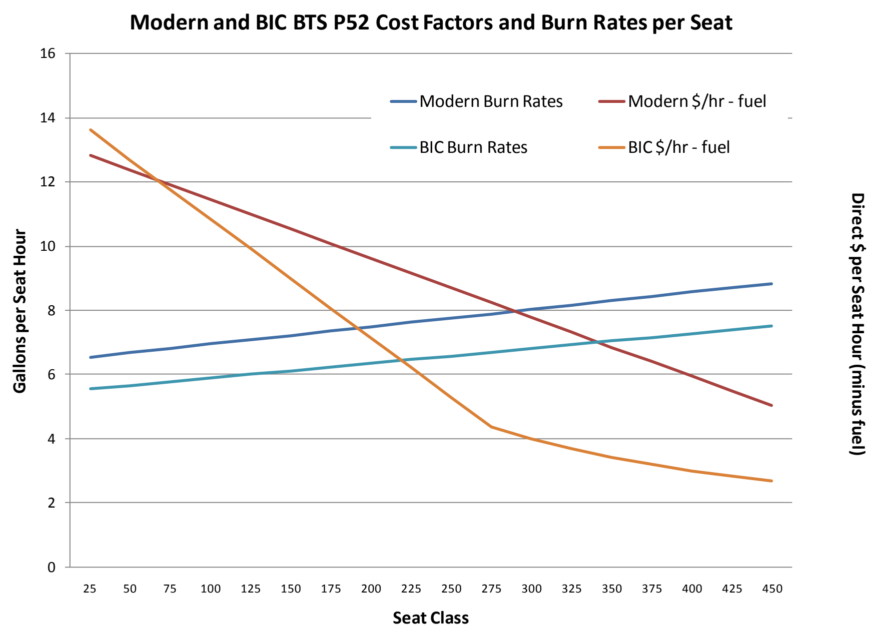



**Figure 70  Modern and BIC BTS P52 cost factors and burn rates per seat**

The flight costs for markets are derived by multiplying the average scheduled flights times from the FAA ASPM database by the aircraft respective cost factors, burn rates and fuel costs as shown below.

Market flight costs = (Direct $/ hr + (Gallons/ hr x Fuel Price) x avg scheduled block times + landing fees

The landing fees applied in the ASOM are shown below in Table 58.

## Table 58 ASOM landing fees

| Class | Avg Weight | Avg Seats | landing fee | $/ seat-landing |
|---|---|---|---|---|
| 25 | 39 | 26 | $ 112 | $ 4.25 |
| 50 | 48 | 50 | $ 137 | $ 2.74 |
| 75 | 76 | 76 | $ 218 | $ 2.86 |
| 100 | 116 | 103 | $ 330 | $ 3.21 |
| 125 | 125 | 124 | $ 356 | $ 2.86 |
| 150 | 129 | 147 | $ 367 | $ 2.49 |
| 175 | 241 | 168 | $ 686 | $ 4.09 |
| 200 | 192 | 204 | $ 546 | $ 2.68 |
| 225 | 332 | 220 | $ 945 | $ 4.30 |
| 250 | 317 | 250 | $ 904 | $ 3.61 |
| 275 | 373 | 270 | $ 1,062 | $ 3.93 |
| 300 | 460 | 305 | $ 1,312 | $ 4.30 |
| 325 | 498 | 327 | $ 1,421 | $ 4.33 |
| 350 | 537 | 350 | $ 1,530 | $ 4.37 |
| 375 | 575 | 372 | $ 1,640 | $ 4.40 |
| 400 | 614 | 394 | $ 1,749 | $ 4.43 |
| 425 | 652 | 416 | $ 1,859 | $ 4.47 |
| 450 | 585 | 452 | $ 1,668 | $ 3.69 |

# APPENDIX D - THE IMPLICATIONS OF AIRLINE ECONOMICS

Recent analysis of airline economics has provided some economic insights for airlines to down gauge their fleets and reduces the average aircraft size per operation in their flight schedules.  The following are economic incentives for airlines to down gauge:

1. Increased frequency of service
2. Increased market share
3. Diseconomies of scale for higher fuel prices
4. Diseconomies of scale for capital investments

This appendix will discuss these economic roadblocks for up-gauging in the airline industry and provide some equations to illustrate the connection of airline costs as a function of seat-hours and airline revenues as a function of seats flown for an airport market.  Finally, this analysis will show how in closed form equations how optimal aircraft size for markets can be derived as a function of average load factor, airfare versus demand equation coefficients, and airline cost equation coefficients.  This analysis will also show how when modeling profit neutral effects of increased operational costs, the impact of these increased costs can be calculated in a closed form.

## D.1 Frequency of Service

Section 2.5 of this dissertation provides a literature review of different demand versus airfare models that are used in the airline industry. Beloboba discusses the impact of airfare and passenger total trip time on passenger demand for a market. (Belobaba et al. 2009) The following formula shows that as airfare increase and or passenger total trip time increases, passenger demand will decrease:

Passenger Market Demand = (market sizing parameter) x (avg price of air travel)$^{a}$ x (total trip time)$^{b}$

Where "a" is the price elasticity coefficient and "b" is the time elasticity coefficient of the passengers for the airport market. These coefficients are mostly negative and represent the percentage change of demand in respect to the percentage change in airfare or total trip time. For example with a price elasticity of -0.7, would indicate that a 10% increase in airfare would result in a (-0.7) x (10%) = -7% change in demand. Elasticities less than -1 are considered elastic because the change in demand will be greater than the change in airfares or total trip time. And elasticities between -1 and o are considered inelastic, because the percentage change in airfares or total trip time will be greater than the change in demand.

Beloboba also shows that frequency of service is related to schedule displacement in the following formula: (Belobaba et al. 2009) Where K is the average wait time for a flight where there is only one flight per day. And Frequency is the number of flights flown to the market each day.

T (schedule displacement) = K/Frequency

Since up-gauging results in reduced frequency of service for a market, the total trip time will increase and demand will reduce. The first economic incentive for airlines to down gauge, is to increase the frequency of service and increase passenger demand. The increased frequency of service postures an airline to handle cancelations and ground delay programs. With smaller aircraft there are fewer passengers to absorb on other flights from a cancellation and more flights in the schedule to accommodate these displaced passengers. And airlines with more frequent flights will have an advantage during ground delay programs.

### D.2 Increased Market Share

Airlines are motivated by competition for profitable markets. The literature review of this dissertation introduced the S-curve which is a model used in the airline industry to represent the interactions between airline frequency share and market share. This model accounts for how competition between airlines affects its market share or percent of demand of the market. The model also captures the effect on airline demand from and incremental increase of frequency of service. (Belobaba et al. 2009)

The S-curve relationship between frequency and market share helps to explain the use by airlines of flight frequency as an important competitive weapon. For example, in a two-airline competitive market, if one airline offers 60% of the non-stop flights it is likely to capture more than 60% of the market share. Conversely, the other airline (with 40% frequency share) will see less than 40% market share. The extent of this disproportionate response of market share to frequency share will depend on the degree to which the S-curve bends away from the market share = frequency share diagonal line.  The postulated S-curve makes immediate intuitive sense at three points on Figure 71:  (1) when an airline offers zero frequency, it will receive zero market share; (2) at 100% frequency share, it must receive 100% market share; and (3) when both carriers offer 50% of the frequency, they should expect 50% market share, again assuming no significant differences in price or other service factors.

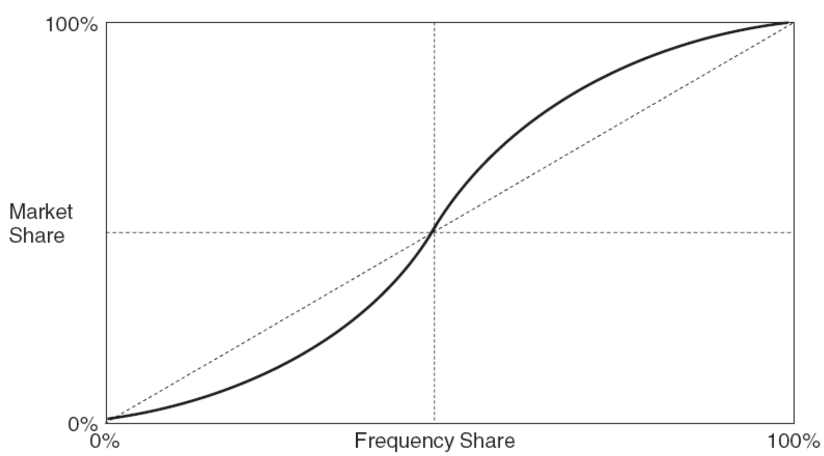



**Figure 71  Market share vs. frequency share S-curve model, figure 3.7 from (Belobaba et al. 2009)**

A study on the impact of aircraft size and seat availability on market share shows negative impacts could be incurred on airlines that choose to up-gauge. (Wei & Hansen 2005) Figure 72 show that increases in capacity through increased service frequency yield approximately equal increases in market share, again the s-curve was not found here. However, increases in capacity through increased aircraft size yield a much smaller increase in market share.

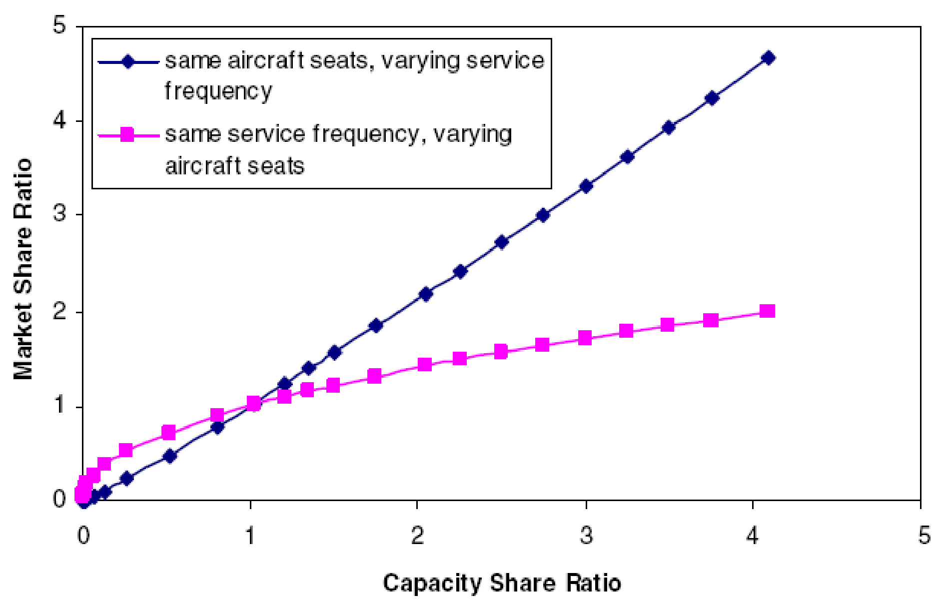



**Figure 72 Changes in market share and capacity share based upon added frequency or aircraft size, figure 2 from (Wei & Hansen 2005)**

The implications of this analysis are that airlines would not receive a proportional increase in market demand from up-gauging their fleet. Therefore, for competitive markets airlines would benefit most from increasing market share with same or smaller size aircraft.

## D.3 Diseconomies of scale for higher fuel prices

Examination of the DOT P52 database has revealed economies of scale exist for non-fuel direct operating costs as a function of aircraft size, measured in terms of seats.(U.S. DOT/BTS 2010) However, diseconomies of scale exist for fuel burn rates as a function of aircraft size. This analysis will show that when fuel prices are between $1 and $2, as has been the case for most of the last couple of decades, as shown in Figure 73.

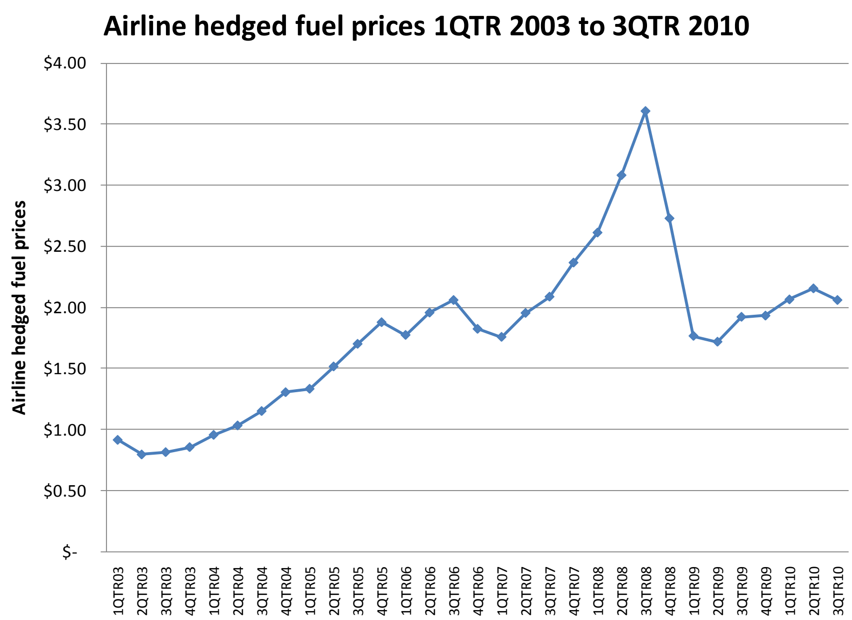



**Figure 73 Airline hedged fuel prices from 1QRT03 to 3QTR10, source P52 database (U.S. DOT/BTS 2010)**

Direct costs for airline operations can be split into variable costs and fixed costs, as shown in chapter 3 of this dissertation. The variable costs are based upon fuel burn and duration of flight and can be expressed as follows:

Direct Operating Costs (Fuel) = Fuel Burn (Gallons/Hour) × Block Hours (Hours) x Fuel Costs ($/Gallon)

When the fuel burn rates are plotted versus aircraft size, it is not surprising to see larger and heavier aircraft burn more fuel per hour of flight time (see Figure 74).

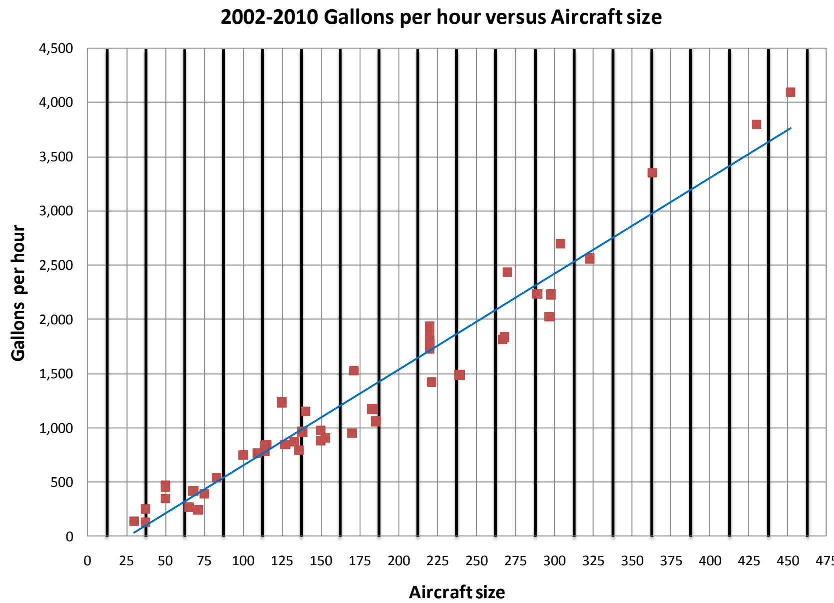



**Figure 74 Average aircraft burn rates (2002-2010) as a function of aircraft seat size, source P52 database (U.S. DOT/BTS 2010)**

To compare fuel efficiency versus aircraft size, direct variable costs can be evaluated per seat-hour as shown below.

Fuel Burn per seat (Gallons/seat-hr) = Fuel Burn (Gallons/Hour) ÷ Aircraft Size (Seats)

This relationship between fuel burn per seat versus aircraft size was found to have approximately a linear relationship, which showed variance based upon the various modernization levels across the fleets. When examining the same aircraft as shown in Figure 74 for gallons per seat-hour versus aircraft size, diseconomies of scale are found (see Figure 75). This analysis shows there is an opportunity for new more efficient aircraft designs between 75 and 125 seat aircraft.

The current principle of aeronautic design, which dictate the larger the aircraft the larger the operational range, is one of the underlying causes for the lack of economies of scale observed in the fuel burn rates per seat or gallons per seat-hour metrics. Possibly designing larger aircraft might flatten this curve out, but should never cause this curve to go negative without an introduction of new technologies like blended wing design.

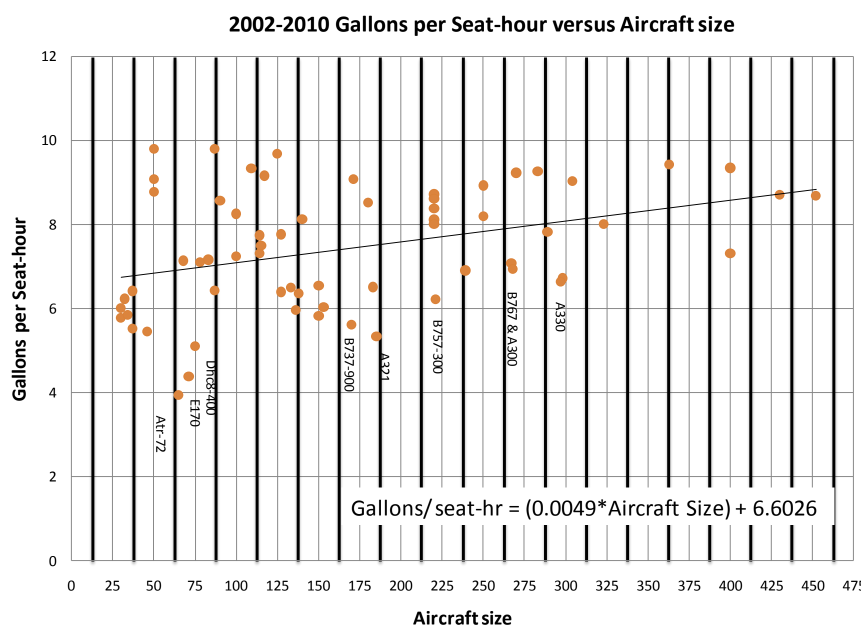



**Figure 75 Average gallons/ seat-hour (2002-2010) as a function of aircraft seat size, source P52 database (U.S. DOT/BTS 2010)**

The examination of Average aircraft gallons per seat hour by seat class from 2002 to 2010 shows very little difference over time, as shown in Figure 76.

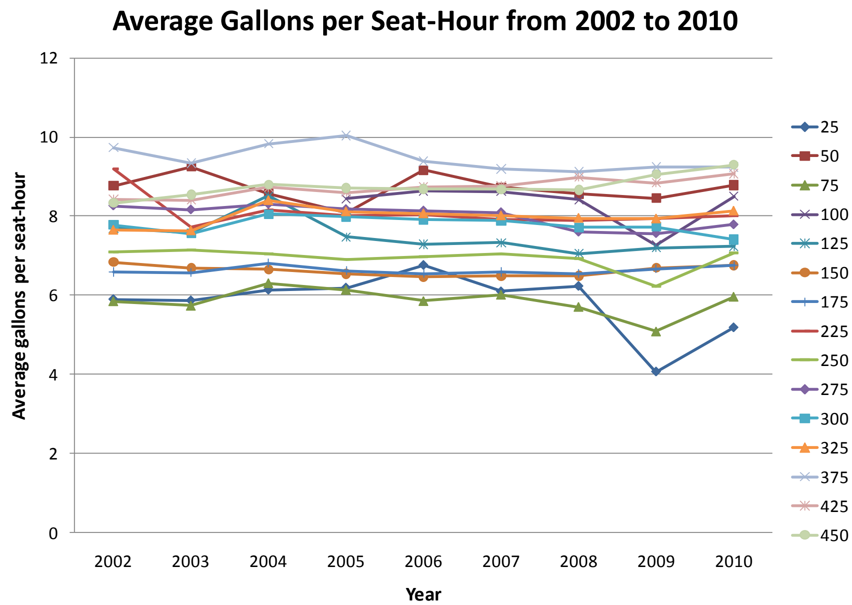



**Figure 76 Average gallons/ seat-hour (2002-2010) for different seat classes, source P52 database (U.S. DOT/BTS 2010)**

This stability allows for the use of multiple years data to derive average aircraft burn rates and gallons per seat-hour. A similar analysis of the variance of aircraft gallons per seat hour within respective seat classes from 2002 to 2010 shows the data has become less noisy over time, as shown in Figure 77. From 2002 to 2005 aircraft in the 50 seat class showed greater variation compared to reporting of these aircraft from 2006 to 2010. From 2006 to 2008 and 2010 the 100 seat aircraft show the greatest variation in gallons per seat-hour.

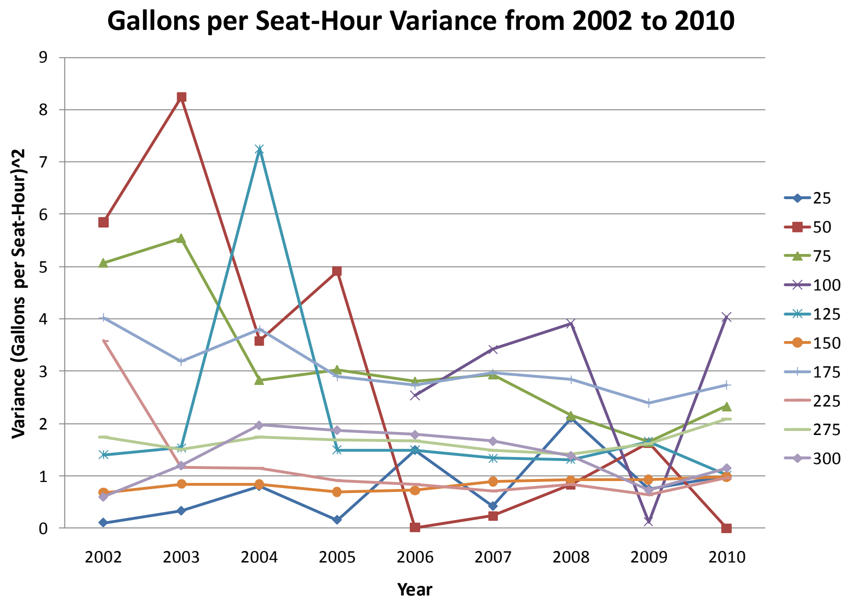



**Figure 77 Variance of aircraft gallons/ seat-hour (2002-2010) for respective seat classes, source P52 database (U.S. DOT/BTS 2010)**

Non-fuel related fixed direct operating costs include personnel costs, aircraft interchange charges, and aircraft rental costs are calculated as follows:

Direct Operating Costs (non-Fuel) = Direct Operating Cost Factor (non-Fuel) ($/hour) × Block Hours (Hours)

Table 59 shows a cost breakdown structure for the P52 database.

**Table 59 Cost breakout of DOT BTS P52 database, source P52 database (U.S. DOT/BTS 2010)**

| | | | | |
|---|---|---|---|---|
| | | **BTS - P52 Database Description and Use** | | |
| | | **Total Aircraft Operating Expense** | | |
| | | Total Flying Operations | Total Flight Equip Maintenance | |
| | | Exp Of Interchange Aircraft | Total Depreciation | |
| | | Amortization Flight Equip | Net Obsoles & Det - Exp Parts | |
| A | **Total Flying Operations** | | **Total Flight Equipment Maintenance** | |
| | Pilots And Copilots | Rentals | Airframe Labor | Engine Labor |
| | Other Flight Personnel | Other Supplies | Airframe Repairs | Aircraft Engine Repairs |
| | Trainees And Instructors | Insurance Purchased | Airframe Materials | Engine Materials |
| | Personnel Expenses | Employee Benefits And Pensions | Airframe Allow Prov | Engine Allow Prov |
| | Prof And Tech Fees And Exp | Injuries, Loss, And Damage | Airframe Overhauls Def, Cred | Engine Overhauls Def, Cred |
| | Aircraft Interchange Charges | Taxes | Aircraft Interchange Charges | Applied Maintenance Burden |
| B | Aircraft Fuel | Taxes | | |
| | Aircraft Oil | Other Expenses | **Total Depreciation** | |
| | | | Airframes | Aircraft Engines |
| | **Non-Cost Relevent Data** | | Airframe Parts | Aircraft Engine Parts |
| | Aircraft Type | Carrier Code assigned by IATA | Other Flight Equipment | |
| C | Total Aircraft Airborne Hours | Aircraft Days Assigned | | |
| D | Aircraft Fuel Issued in gallons | Year | **Other Depreciation and Amortization (Non-Flight Equipment)** | |
| | | Quarter | No data reported | |
| | 25% or less missing | b/w 25% and 50% missing | b/w 50% and 75% missing | more than 75% missing |
| | | **Calculated by Quarter and by Aircraft Group (by multiples of 25 seats)** | | |
| | | Direct Cost (minus fuel) per flight hour = (A-B)/C | | |
| | | Fuel Burn Rate per flight hour = D/C | | |
| | | Average cost of fuel per gallon = B/D | | |

When the non-fuel direct operating costs are plotted versus aircraft size, it is not surprising to see larger and heavier aircraft cost more per hour to operate (see Figure 78).

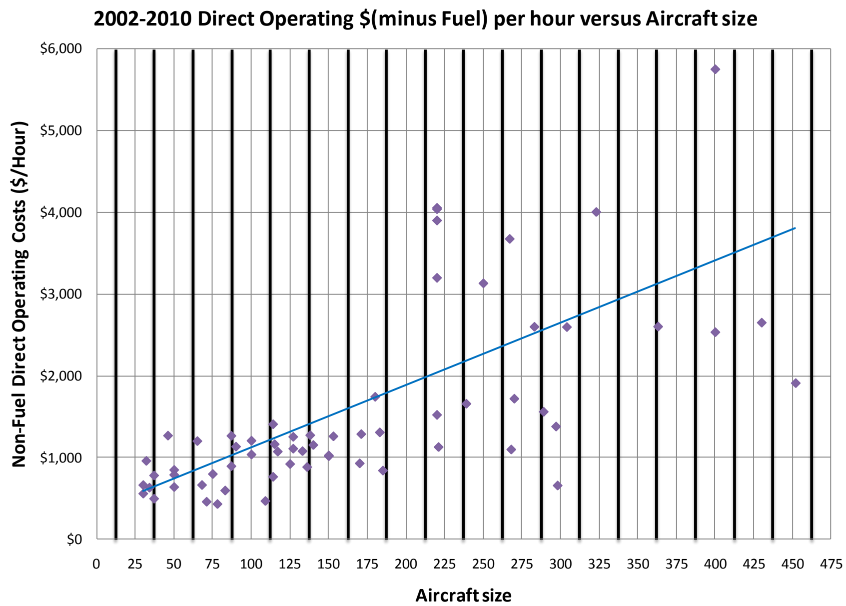



**Figure 78 Average aircraft non-fuel direct cost factors (2002-2010) as a function of aircraft seat size, source P52 database (U.S. DOT/BTS 2010)**

To compare fuel efficiency versus aircraft size, direct fixed costs can be evaluated per seat-hour as shown below.

Non-fuel cost factors per seat ($/seat-hr) = Direct Operating Cost Factor (non-Fuel) ($/hour) ÷ Aircraft Size (Seats)

This relationship between fixed direct operating costs per seat versus aircraft size was found to have approximately a linear relationship. When examining the same aircraft as shown in Figure 78 for non-fuel cost factors per seat ($/seat-hr) versus aircraft size, economies of scale are observed (see Figure 79).

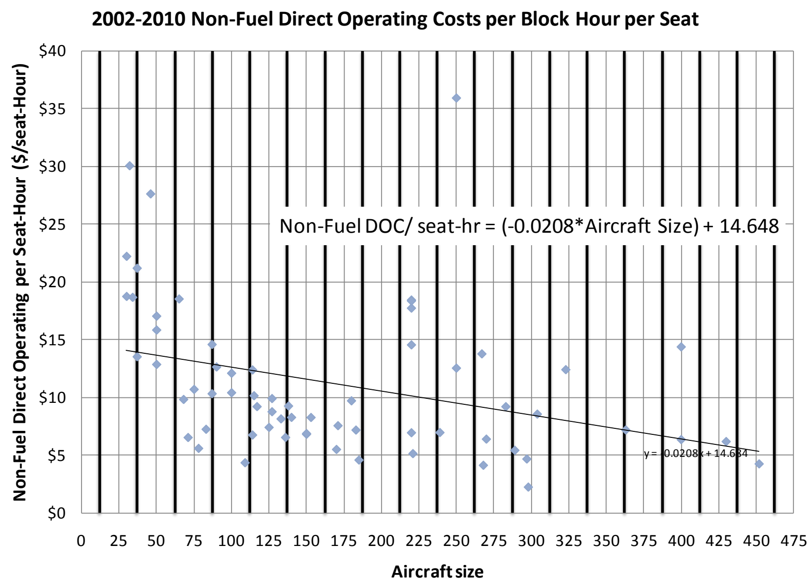



**Figure 79 Average non-fuel $/ seat-hour (2002-2010) as a function of aircraft seat size, source P52 database (U.S. DOT/BTS 2010)**

The examination of Average aircraft non-fuel direct costs per seat hour from 2002 to 2010 shows very little difference over time, as shown in Figure 80. This stability allows for the use of multiple years data to derive average aircraft non-fuel direct costs per seat hour.

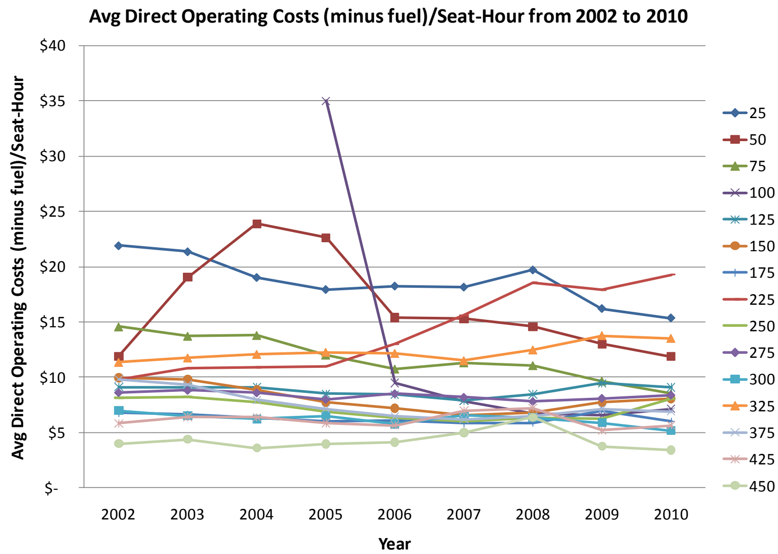



**Figure 80 Average aircraft non-fuel $/seat-hour (2002-2010) for different seat classes, source P52 database (U.S. DOT/BTS 2010)**

A similar analysis of the variance of aircraft non-fuel direct costs per seat hour within respective seat classes from 2002 to 2010 shows the data has become noisier over time, as shown in Figure 81. For 2004 and 2005 aircraft in the 50 seat class showed greater variation compared to reporting of these aircraft from 2006 to 2010. From 2002 to 2010 most aircraft seat classes show the variation in non-fuel direct costs per seat hour increasing, especially for aircraft reported in the 225 seat class.

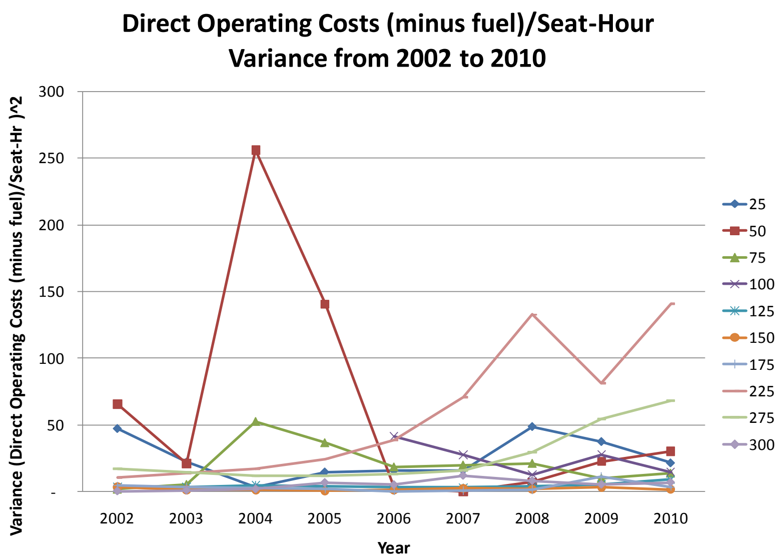



**Figure 81 Variance of aircraft non-fuel $/seat-hour (2002-2010) for respective seat classes, source P52 database (U.S. DOT/BTS 2010)**

The signal to noise, mean divided by variance (**μ/σ**), analysis of the direct operating costs per seat-hour is shown in Figure 82. This analysis shows a much greater signal to noise for reported fuel consumption versus non-fuel direct operating costs.

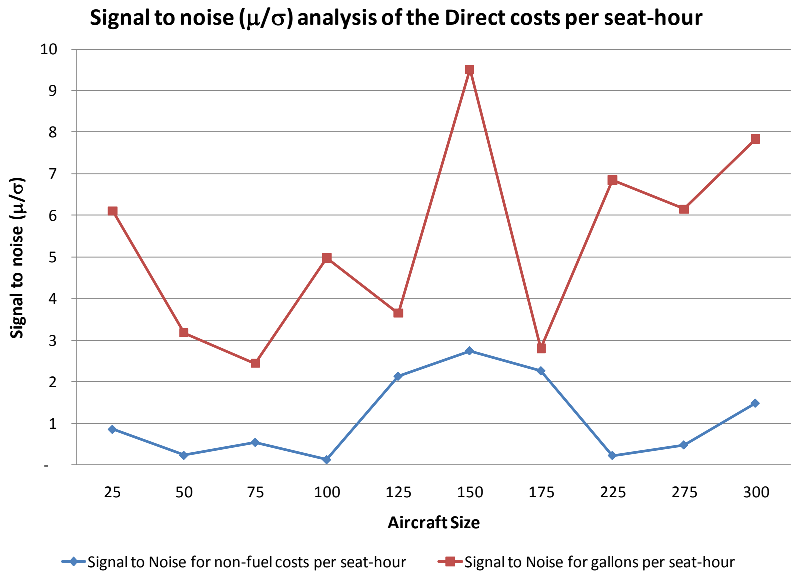



**Figure 82 Signal to noise (μ/σ) analysis of the Direct costs per seat-hour (2002-2010) for respective seat classes, source P52 database (U.S. DOT/BTS 2010)**

Lastly, Figure 83 shows an examination of the combined fuel and non-fuel direct operation costs for different fuel prices. This analysis shows that economies of scale exist at $1 fuel prices, these economies of scale disappear around $3 fuel prices, and diseconomies of scale exist at $5 fuel prices as shown by the respective negative, flat and positive slopes. While these underlying diseconomies of scale have existed for some time now, they do not change overall economies of scale until fuel prices increase beyond $2 per gallon. Since fuel prices may never go below $2 per gallon again for airlines, the airline industry must recognize these reduced economies of scale and potential diseconomies of scale when analyzing airline economics. Therefore, these diseconomies of scale at higher fuel prices will incentivize airlines to down gauge.

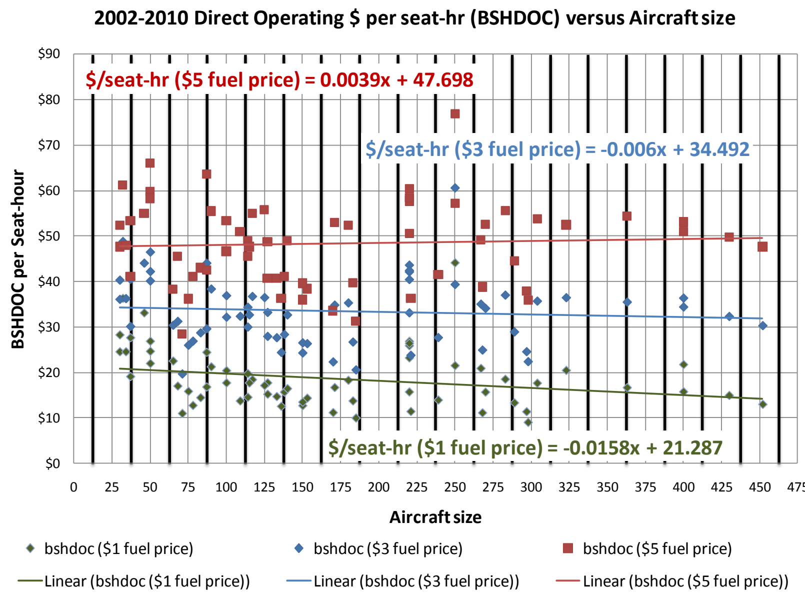



**Figure 83 Direct operating costs per seat-hour (2002-2010) for respective seat classes at ($1, $3, and $5 fuel prices), source P52 database (U.S. DOT/BTS 2010)**

## D.4 Diseconomies of scale for capital investments

The 2008 acquisition costs for narrow body and wide body aircraft show diseconomies of scale as well. (Belobaba et al. 2009) Therefore, airlines receive operational benefits from down gauging for higher fuel prices and they receive strategic benefits from lower capital costs per seat, as shown in Table 60.

**Table 60 Diseconomies of scale in aircraft acquisition costs, source (Belobaba et al. 2009)**

| Type of Aircraft | Acquisition Cost/ unit | Seats | Acquisition Cost/ seat |
|---|---|---|---|
| typical twin-engine, narrow-body, 150-seat aircraft | $50-$60 Million | 150 | $0.3 to $0.4 Million |
| long-range, wide-body aircraft such as the Boeing 747-400 with over 400 seats | $225 Million | 400 | $0.52 Million |
| Airbus 380 aircraft, which can seat up to 600 passengers | $300 Million | 600 | $0.5 Million |

## D.5 Airline Profit Model as a function of seat size, willingness to pay parameters and economy of scale parameters

Examining these economies and diseconomies of scale for aircraft, provides motivation to further connect the dots by seeing if equations can be used to describe optimal seat sizes of aircraft as a function of willingness to pay (demand versus airfare) parameters and airline cost parameters. Once this functional form is identified then analysis can be done to see how fluctuations in fuel prices affect the coefficients of these functions. The following section will provide the formulations of these functions.

### D.5.1 Airline Profits as a function of seat size

The basic airline profit equation is defined as revenue minus cost, which can be expressed in the following form: (Belobaba et al. 2009)

Operating profit = Revenue Passenger-Kilometers (RPK) × Yield – Available Seat-Kilometers (ASK) × Unit cost

Revenue is also defined as Demand (D)*Average Airfare (P). Since demand can be defined by average load factors (LF) * Seats per operation (S), revenue can be rewritten as Revenue = LF*S*P

Chapters 2 and 3 introduce the gravity and exponential demand versus airfare models, which are two of the models currently used in the airline industry. This analysis will show that both models can be used to formulate the desired equations. To include the parameters of these equations, first airfare will be defined in terms of these parameters.

A simplified version of the Gravity equation is as follows – Demand (D) = $M \times P^a$

M is defined as a Market Demand Coefficient, which represents the maximum potential demand for a market with airfares of $1. P is the average market airfare as defined earlier. And "a" is the price elasticity of the market. If we solve for P below:

$D = M \times P^a$, $P^a = D/M$, $P = (D/M)^{1/a}$, $P = (LF*S/M)^{1/a}$

The revenue equation can now be written as a function of average seat size, average load factor, and the market gravity model parameters M and a.

Revenue = LF*S*P = LF*S*(LF*S/M)$^{1/a}$

An exponential representation of the demand model is as follows – Demand (D) = N x exp$^{b*P}$

N is defined as a Market Demand Coefficient, which represents the maximum potential demand for a market with airfares of $0. P is the average market airfare as defined earlier. And b is the price coefficient for the market. If we solve for P below:

D = N x exp$^{b*P}$, ln(D) = ln(N) + b*P, b*P = ln(D) – ln(N), P = (ln(LF*S) – ln(N))/b

The revenue equation can now be written as a function of average seat size, average load factor, and the market gravity model parameters N and b.

Revenue = LF*S*P = LF*S*(ln(LF*S) – ln(N))/b

Earlier discussions of direct operating costs illustrated that fuel burn rates per seat and non-fuel direct operating costs per seat-hour could be described as a linear function. Therefore fuel operating costs for an aircraft can be written as (f0 + f1 * Seats)*Seats*fuel price*flight hours. F0 and f1 are the intercept and slope of the linear approximation of aircraft fuel burn rates per seat. Non-fuel direct operating costs per seat-hour can be written as (g0 + g1 * Seats)*Seats*flight hours. G0 and g1 are the intercept and slope of the linear approximation of aircraft fuel burn rates per seat. Therefore direct operating costs can be represented by the following function:

Direct Operating Costs = [ (f0 + f1 * Seats) *fuel price (FP) +(g0 + g1 * Seats)]*Seats *flight hours (H)

Direct Operating Costs = [ (f0 + f1 * S) *FP +(g0 + g1 * S)]*S *H

Now that both revenue and costs are defined by seats, these two formulations can be combined.

Profit = Revenue – Costs (Exponential)

Profit = LF*S*P = LF*S*(ln(LF*S) – ln(N))/b – [ (f0 + f1 * S) *FP +(g0 + g1 * S)]*S *H

Next the most profitable aircraft size can be determined by taking the derivative of this profit equation to respect of Seats or S and setting the equation equal to zero.

D P/ d S = LF*(Ln(LF*S)-Ln(N))/b + ($LF^2$)/b – [(f0 + 2*f1*S)*FP + (g0 + 2*g1*S)]*H = 0

= LF/b*Ln(LF*S) – LF/b*Ln(N) + ($LF^2$)/b – 2*S*H*(f1*FP + g1) – H*(f0*FP + g0) = 0

2*S*H*(f1*FP + g1) – LF/b*Ln(LF*S) = - LF/b*Ln(N) + ($LF^2$)/b – H*(f0*FP + g0)

Since the range of LF*S for most commercial aircraft will be between 20 and 600, the possible range for ln(LF*S) will be 3 to 6. So by approximating ln(LF*S)=4, we are still able to understand how the optimal seat sizes for airlines will change as a function of the parameters in the market demand versus airfare curve and the parameters in the fuel burn per seat and non-fuel direct costs per seat-hour equations.

2*S*H*(f1*FP + g1) – LF/b*4 = - LF/b*Ln(N) + ($LF^2$)/b – H*(f0*FP + g0)

2*S*H*(f1*FP + g1) = LF/b*(4-Ln(N)) + ($LF^2$)/b – H*(f0*FP + g0)

$S \approx [LF/b*(4\text{-}Ln(N)) + (LF^2)/b – H*(f0*FP + g0)]/[2* H*(f1*FP + g1)]$

For an example market SFO-ATL where

b = -0.007646281,ln(N) = 11.3 , LF = 0.9, FP =$2, f0 = 6.6026, f1 = 0.0049, g0 = 14.648, g1 = -0.0208, and H = 5 hours

Therefore, S $\approx$ -5589 or in other words airlines are economically encouraged to down gauge to as small of an aircraft that is feasible for the market.

A similar approach with the gravity equation is shown below:

Profit = Revenue – Costs (Gravity)

$Profit = LF*S*(LF*S/M)^{1/a} – [ (f0 + f1 * S) *FP +(g0 + g1 * S)]*S *H$

$d\ Profit/ d\ S = (1+a)*LF^2*S^{1/a}/M – [(f0 + 2*f1*S)*FP + (g0 + 2*g1*S)]*H$

set equal to zero and solve for S

$2*S*H*( f1*FP + g1) = (1+a)*LF^2*S^{1/a}/M – H*[f0*FP + g0]$

$2*S^{(a-1)/a}*H*( f1*FP + g1)= (1+a)*LF^2 /M – H*[f0*FP + g0]$

$S^{(a-1)/a} = [(1+a)*LF^2 /M – H*(f0*FP + g0)]/[2* H*( f1*FP + g1)]$

$S = [[(1+a)*LF^2 /M – H*(f0*FP + g0)]/[2* H*( f1*FP + g1)]]^{a/(a-1)}$

Since anything divided by the big M is approximately zero

$S \approx [[-H*(f0*FP + g0)]/[2* H*( f1*FP + g1)]]^{a/(a-1)}$

For an example market SFO-ATL where

a = -3.38, FP =$2, f0 = 6.6026, f1 = 0.0049, g0 = 14.648, g1 = -0.0208, and H = 5 hours

S ≈ 248 seats

### D.5.2 Adjusting willingness to pay parameters in response to increases in operational costs for profit neutral conditions

For profit neutral conditions (with fixed LF, M, & S)

Revenue (New) – Revenue (Old) = Cost from $1 fuel price change

LF*S*(Ln(LF*S)-Ln(M))/anew – LF*S*(Ln(LF*S)-Ln(M))/ aold =

(v0 + v1 * S)*S*fuel price*Block Hours

LF*S*(Ln(LF*S)-Ln(M))/anew = LF*S*(Ln(LF*S)-Ln(M))/ aold +

(v0 + v1 * S)*S*fuel price*Block Hours

a new = LF*S*(Ln(LF*S)-Ln(M))/[LF*S*(Ln(LF*S)-Ln(M))/ aold + (v0 + v1 * S)*S*fuel price*Block Hours]

## D.6 Application of findings for Macro Economic Models of Airline Operational Behavior

The current principle of aeronautic design, which dictate the larger the aircraft the larger the operational range, is one of the underlying causes of the lack of economies of scale observed in the fuel burn rates per seat or gallons per seat-hour metrics. Possibly designing larger aircraft might flatten this curve out, but should never cause this curve to go negative without an introduction of new technologies like blended wing design.

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# Curriculum Vitae

Lieutenant Colonel John Ferguson received his Bachelor's degree in Mathematics from Virginia Military Institute in 1988 and his Master's degree in Physics from Memphis State University in 1990. He has worked over 21 years as a programmer analyst, a systems engineer and an operations research systems analyst for the Department of Defense. Currently, he is working at the Center for Army Analysis (CAA) as an operations research systems analyst. He has published over 13 papers, and briefed his work at national conferences.