ABSTRACT

Title of Thesis:	AGGREGATE STATISTICAL MODELS FOR NATIONAL AIRSPACE SYSTEM PERFORMANCE
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With the ever increasing congestion at airports around the world, measuring and modeling the airspace system performance metrics poses one of the most important challenges for any strategic decision support system. The Federal Aviation Administration and the airlines have been striving to improve utilization of the critical resources to improve performance.

This thesis develops theoretical models to understand the performance of national airspace system measured in terms of both flight level and passenger level. This thesis will address modeling the flight cancellation probability and flight delays in the National Airspace System for an aggregated time period and use them to predict average passenger delays. It will also showcase avenues for future applications of such theoretical models to improve prediction of the airspace congestion and thereby improve decision making capability in aviation systems.

AGGREGATE STATISTICAL MODELS FOR
NATIONAL AIRSPACE SYSTEM PERFORMANCE

By

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Thesis submitted to the Faculty of the Graduate School of the
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Advisory Committee:
Professor Michael O. Ball, Chair
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DEDICATION

I dedicate this endeavor to my parents, my brother and my sister, who have been the constant driving force in my pursuit of knowledge.

Acknowledgements

First, I will like to express my gratitude to Dr. Michael Ball for all his guidance, encouragement and unending patience throughout the course of my work at NEXTOR. Working with him has been extremely educational and enjoyable. I extend my gratitude to Dr. Avijit Mukherjee for his insight and for the countless hours he spent helping me to plow through the details. I will like to thank Dr. David Lovell and Dr. Robert Hoffman who provided me with necessary insights towards the development of the models. I really appreciate everyone's willingness to assist me whenever I needed it.

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Chapter 1: INTRODUCTION

1.1 Air Traffic Overview

Air traffic in the United States has seen phenomenal growth in the past few decades. It has evolved from being a small industry into a key economic driver employing over 1.7 million people in the United States. Current projections indicate that air traffic will grow at an annual rate of 3 - 5% over the next 12 years. Unfortunately, the growth in air traffic has not been marked by a corresponding increase in airport resources. As a result, the level of congestion has risen, leading to staggering delays during peak periods of activity. The disproportion between stagnating capacity and ever-increasing demand has (and will have) enormous consequences on the performance of the air transportation system.

1.2 The National Airspace System

This section introduces the structure of the national airspace system and some of the terms in Air Traffic Management (ATM). The National Airspace System (NAS) is managed by the Federal Aviation Administration in cooperation with the airspace users, and consists of the overall airspace and airport environment for the operation of aircraft. The NAS is comprised of the aircraft, airports, maintenance personnel, airline dispatchers, tower controllers, terminal area controllers, enroute controllers and oceanic controllers. Also parts of the NAS are the computers, communication equipments, satellite navigation aids and radars.

Airspace refers to the physical space in which the aircraft moves along. Since the aircraft moves through a system of constrained runways and waypoints (servers), the NAS can be viewed as a complex queuing network. The NAS is highly stochastic. Accurate information regarding future airport and en-route capacities and demand are never available.

Airspace capacity has been unable to keep pace with the growth in demand and traffic. This has resulted in congestion in the airspace and in airports – resulting in delays. [1] stated that to avert unacceptable levels of congestion, the following directions could be followed:

1. Increase in capacity through new airports and runways
2. Better air traffic management in strategic and tactical levels
3. Demand management at airports

Capacity cannot be changed in a short period of time and is not always an acceptable solution to the congestion problem. This motivates the need to develop computationally inexpensive models to predict performance metrics for the NAS to understand the impact of congestion and other such factors.

1.3 National Airspace System Strategy Simulator

The National Airspace System Strategy Simulator is being developed by the FAA as a decision support system to evaluate long-term infrastructure and regulatory strategies. The goal is to provide feedback to FAA planners and decision makers on the impact of new technologies, new operational concepts and other major systems changes. The decision support capability when institutionalized is intended to support such efforts as the FAA strategic plan and the Joint Planning and Development Office (JPDO) analysis of the NAS beyond 2015. Its overall goal is to support the operating entities in the FAA, and all the constituents within the NAS, can make decisions consistent with an integrated performance based management approach to future development.

The NAS strategy simulator consists of several components with different constraints embedded in a feedback loop so as to understand the system-wide effects. In designing the Strategy Simulator model, the National Airspace System is conceived as comprising of three interacting sectors: passengers and shippers, fleets of aircraft and their operators, and the system of airports and air traffic control (ATC). Aircraft fleets draw on services of the airports and ATC in order to provide, in turn, services to passengers and shippers.

- Aircraft fleet operators offer to passengers and shippers the opportunity to take trips, associated with prices and travel times. Passengers and shippers use some or all of that capacity and in exchange provide money to the fleet operators.

- Airports and ATC offer fleet operators the opportunity to fly flights. The aircraft fleet operators use some or all of that capacity and in exchange they provide money through fees and taxes.

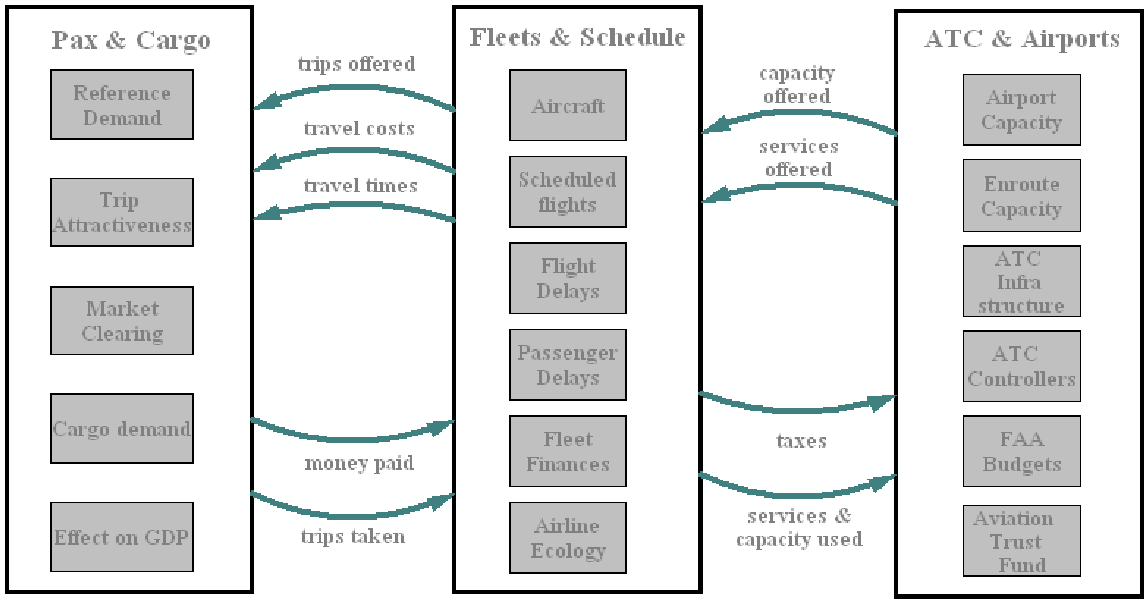

Figure 1 : Overview of NAS Strategy Simulator

Each sector is represented in the model as a collection of modules computing the status of different aspects of the overall system and also the interactions with the other modules.

The NAS strategy simulator can be used to address a wide-range of questions. Benefits of policy decisions on long-term effects can be evaluated. Specific scenario to be evaluated are given as input and based on the models built using historical data, the simulator produces the necessary output – in the form of numbers, tables and charts. Another approach would be to focus on a specific output and carry out simulations to determine the input that most likely lead to the desired output.

The major inputs for the Strategy Simulator can be broadly categorized into:

- FAA policies and fee structures (landing cost, taxes, cost of slots, etc)

- Airport policies and fee structures (infrastructure cost, cargo handling, etc)
- Economic & political environment (Inflation, GDP, etc)
- Technology availabilities (technology for controllers, ATC operations, etc)

Using the inputs, some of the major outputs for the Strategy Simulator are:

- Capacities of the NAS(Dependent on controllers available, slots available,)
- Demand levels for air travel (using capacity, number of flights flown. etc)
- Air travel experience (dependent on flying time, waiting time etc)
- Airlines: number, behavior and policies, financial health (using operating costs, taxes levied, profit/loss made)
- Fleet mix: number of various types of aircraft in use (depends on demand, landing cost etc)
- Demands on ATC system: operations, peaks, hubs (depends on airline behavior, number of flights flown, weather condition, etc)
- ATC personnel: productivity, experience levels, number required
- ATC technology: installed base of various technologies
- FAA finances and trust fund

The NAS Strategy Simulator, with the above inputs and outputs, will be able to address an enormous range of questions. Some of the questions are:

- Given fleet mix, demand on the system, what will future airspace demand look like?
- What will demand be for Air Traffic Controllers?
- Which ATC technologies would, if widely adopted, most help the performance of the entire NAS?
- Given any specified set of FAA policies, which technologies will become widely adopted?
- Evaluating the simulated performance of the system as measured using the above outputs, if new technologies could be brought online more quickly, and adopted more quickly by airlines and airports, how much improvement in NAS performance and FAA finances could be expected?
- Considering increase in demand, what will future ATC personnel requirements be?
- What FAA policies should be adopted to maximize NAS performance?
- What would be the effect of changing the basis and magnitude of fees and ticket taxes?
- What will the passenger air travel experience be like (delays, segments per trip, cost)?
- Given increase in demand and using delay levels, what will future aircraft mix look like?

1.4 Problem Description

The steady rise in demand for air transportation has emphasized the need for improved air traffic flow management (TFM) within the National Airspace System. Examples of TFM initiatives in response to weather conditions and excessive traffic volume such as ground stops include ground delay programs, rerouting, airborne holding, and miles-in-trail restrictions. These initiatives seek to control the air traffic demand to mitigate the demand-capacity imbalance due to the reduction in capacity, result in NAS delays [4]. To guide flow control decisions during the operations, and for post operations analysis, it is imperative to create a NAS performance model that characterizes the relationship between various factors that affect them.

Our study is part of a high-level decision support tool for the Federal Aviation Administration to analyze the impact of new technologies for the entire National Airspace System and devise new operational concepts and procedures. Some examples of problems addressed are the right combination of demand management and infrastructure investments, whether or not to build a runway to increase airport capacity, how to accommodate high demands, and the impact of introducing sophisticated new Air Traffic Control technology [2]. The FAA is moving toward a performance based organization concept to make the Air Traffic Control (ATC) system more responsive to the nation. The need for a decision support system to guide this transformation is even more acute in a period of continued economic slowdown. [3]

The Federal Aviation Administration and others are using complex computer models to analyze National Airspace System performance. The NAS strategy simulator is aimed at a mere aggregate level in order to evaluate performance metrics over large time horizons for policy level questions. No satisfactory aggregate models for delays and cancellations exist. An aggregate model should be independent of individual airports but yet characterize various airport characteristics. Also, the model should include long-term effects of various factors that impact performance adversely. One such factor is en-route convective weather. Bad weather causes the reduction of airport arrival and departure capacity resulting from reduced visibility, ceiling, and, to some extent, surface winds (i.e., surface weather). In adverse weather conditions, Instrument Flight Rules(IFR) are used leading to decreased arrival rates.

The NAS performance models take as input information on NAS capacity and demand and output estimates of NAS performance. The objective of the NAS performance models is to estimate the relationship between explanatory variables related to demand and capacity, and the performance metrics. NAS performance is measured at both a flight level and a passenger level. At the flight level the two quantities of interest are average flight delay and flight cancellation probability. At the passenger level, we consider average anticipated delay and average unanticipated delay.

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Airports possess limited capacity to handle aircraft arrivals and departures. The capacity, generally measured in operations per hour, depends on basic airport characteristics, including technology available, numbers of runways and runway layout, to name a few [4]. It also varies over time and conditions, based on factors such as weather conditions, runway configuration in use, mix of operations (arrivals vs departures), mix of aircraft types as well as other factors. Another factor is whether Visual Meteorological Condition (VMC) or Instrument Meteorological Condition (IMC) exist? For example, at San Francisco International airport (SFO), under VMC, aircraft can make side-by-side approaches into the airport's two parallel runways, whereas under IMC this is not possible. Thus, IMC capacity is approximately ½ of VMC capacity.

On-Time Performance of passenger trips is one of the critical performance measures of the quality of service provided. Also on-time performance is a significant factor in the service-profit chain that drives airline profitability, productivity and customer loyalty and satisfaction. For a given flight, passenger trip time is determined by flight times, as well as the time accrued by passengers following missed connections and cancellations. Knowledge of delays are used for aircraft maintenance compliance and crew salary calculations. See [5] and [6].

This motivates us to estimate passenger delay in order to better measure passenger schedule reliability and also understand about passengers who are disrupted in real-time because of their flight getting cancelled or flight getting delayed by so much that they miss their connecting flight.

The strategy simulator will contain a list of airport classes. Tracking the congestion separately for different airport groups will allow the model to investigate the impact on trip attractiveness.

The framework of our study integrates three models that relate demand and capacity for national airspace system performance in terms of average flight delay, probability of flight cancellation and average passenger delay.

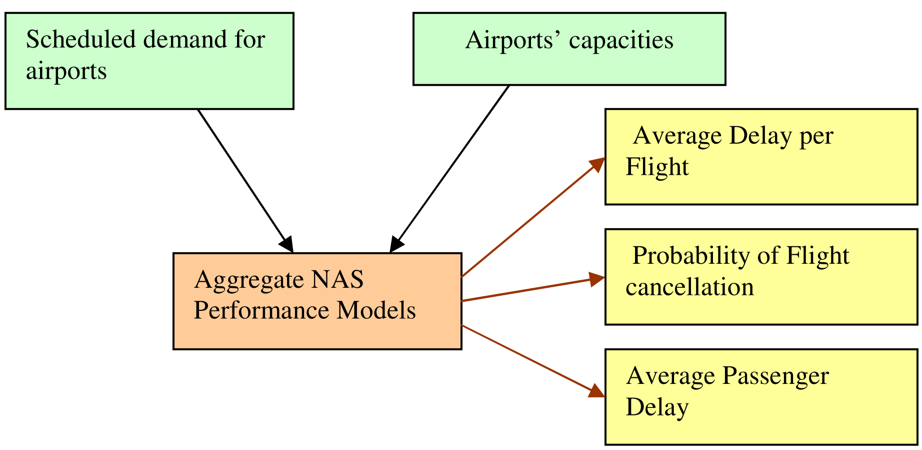


Figure 2 : NAS performance metrics

1.5 Literature Overview

An extensive literature review was conducted of models for NAS performance metrics to provide a full overview of foundation for the models developed in this thesis. We also reviewed general concepts underlying Air Traffic Management (ATM).

A basic aggregate model for NAS delay was developed in [2]. Wieland used a queuing model to estimate the capacity of the NAS. A single variable is used to predict delay - traffic count. The drawback of the model is that it can account for only a small portion of the factors that impact delay. The expected upward trend in delay as traffic grows is evident.

In [7] daily delays and cancellations to support strategic simulations were modeled. This research takes into consideration delay propagation effects. Both cancellation probabilities and delays are estimated. The models provide estimates for a single airport.

Several efforts have been made during the past few years to understand the connection between weather and delay both at the local and national level The concept of the Weather Impacted Traffic Index (WITI), which estimates the impact of weather on planned traffic flows, was introduced in [1]. [8] developed computational methods for WITI using extended regions around severe weather cells, and a set of statistical features, histogram based features, and time-domain features of WITI time histories. These produced good correlation between estimated and reported NAS delays.

[9] extended Chatterji's work with a goal of establishing an empirical relation between weather, traffic and NAS delays, in order to measure the operational delay performance of NAS.

[3] has developed a regression model of NAS delay for the FAA where lightning strike data was used to characterize en-route weather.

In [10] , further work on weather impacted traffic index(WITI) has been carried out. The new weather index has a quantification methodology that can analyze outcome variability. The metric computed in the paper used both en-route and terminal components.

In [11], research on flight schedule reliability resulted in estimating passenger trip delay. He analyzed the impact of disrupting activities on passenger trip time using proprietary airline data to investigate the impact of delayed flights, cancelled flights and missed connections, on passenger trip time. The limitation of research in [5] is that all the results are constrained by one-month (August 2000) based on proprietary passenger booking data provided by a single airline.

[6] measured the Air Transportation System on-time performance from a passenger's perspective. The paper tries to understand and predict impacts on passenger trip delay given anticipated changes in the future. Simulation algorithms

were developed to use publicly accessible flight-based databases to convert flight data to passenger trip data.

1.6 Organization of Thesis

Chapter 2 contains information on data sources and preliminary data undertaken prior to formal analysis. It also provides information on the trends in airspace performance, with respect to delay and cancellation rate in the NAS.

Chapter 3 provides details about the model, the underlying theory analyzes some of the major factors that affect NAS performance. The various metrics developed are described and their significance is discussed. This chapter also provides motivation for categorizing airports for aggregate models to evaluate performance.

In Chapter 4, we develop theoretical models based for NAS performance metrics. The results of the model estimation are presented. The models created are validated by applying them to real-world data.

In Chapter 5, the main contributions of this thesis are summarized. We also evaluate potential areas in air traffic management where the concepts behind these models can be applied for increased efficiency in the system.

Chapter 2: PROBLEM DESCRIPTION

2.1 Overview

In this chapter, the NAS performance over the years is studied. The following three performance metrics are analyzed :

- Average Flight Delay
- Flight Cancellation rate
- Average Passenger Delay

The air transportation system is a significant contributor to the national economy in the form of direct, derived and induced effects. For example, employment and taxes are severely impacted because of air transportation system. (One such system is the freight handling system – which relies heavily on air transportation). Forecasts of demand for air transportation predict significant increases in passenger enplanements, cargo and aircraft operations. Analysis of the performance of the NAS under current levels of operations indicates that without increases in capacity, delays and cancellations and hence passenger delays are expected to grow.

2.2 Problem Definition

The three performance metrics for the NAS are to be modeled. Aggregate econometric models for flight delays, flight cancellation probabilities and passenger delays are to be created.

Flight delays can be attributed to queuing effects within the air transportation network. As delays in air transportation system worsen, more and more people switch to another mode of transportation.

The steady rise in demand for air transportation has demonstrated the need for improved air traffic flow management within the National Airspace System. One of the metrics that has been used to assess the performance of NAS is the actual aggregate delay. Flight delays, in many cases, are caused by the application of TFM initiatives in response to weather conditions and excessive traffic volume. TFM initiatives such as ground stops, ground delay programs, rerouting, airborne holding, and miles-in-trail restrictions, are actions that are needed to control the air traffic demand to mitigate the demand-capacity imbalances due to the reduction in capacity. Consequently, TFM initiatives result in NAS delays. Of all the causes, weather has been identified as the most important causal factor for NAS delays. Therefore, to guide flow control decisions during the day of operations, and for post operations analysis, it is useful to create a baseline for NAS performance and establish a model that characterizes the relation between weather and NAS delays. Hence given the demand and expected weather, the model can be used to predict the expected aggregate delay.

Flight cancellation probability is defined as the probability that a flight scheduled will be cancelled. Airlines usually cancel their flights when they experience non-availability problems related to crew, maintenance and security personnel, ATC problems like runway breakdowns etc, and weather related problems that reduce the airport capacity. Before canceling a flight, the airlines would weigh the economics – fuel costs saved for the cancelled flight versus cost incurred due to passenger delays and loss of goodwill - and then make a decision whether to cancel a flight or not. In most cases, decisions related to cancellations are affected by circumstances outside the control of airlines (e.g. weather problems and reduction of airport capacities). In some cases, airlines might face an operational problem that forces the cancellation of a particular flight. However, many times airlines can exercise some control which flights are cancelled and the number of flights cancelled after considering economic trade-offs. But, whatever the reasons, the airlines have the responsibility to provide their updated flight plans to the ATC system so that airport resources can be better used in lieu of flight cancellations. Since flight cancellations mean a significant loss to the airlines, it becomes of paramount significance to model them accurately.

Flights delayed or cancelled adversely affect the passengers. Loss of Productivity (or Passenger Time Value) represents a valuation of the loss of passenger time value contributed to U.S. economy due to bad quality of service. Passenger delay is the actual delay passengers experienced by disrupting aviation activities, including both flight delay and cancellations. Delay and cancellation are essentially the same from the passenger perspective. They both impose delays to travel time. Generaly, cancellations generate extremely high passenger delays. In order to estimate passenger delay, transformations must be applied to convert the number of cancellations into delay of relocated passengers on the cancelled flights. Thus the total passenger delay includes not only delays obtained from delayed flights but also delays induced by cancellations.

2.3 NAS Performance over the years

2.3.1 Flight Cancellations

Using the data obtained from ASPM database, the following plot shows the probability of cancellation in NAS from January 2000 to December 2004. There has been a mild decreasing trend over these years. Probability of cancellation is the average of total cancelled flights over total scheduled flights across all major airports in a given time horizon. (Here, we have computed for the 35 OEP airports for each month).

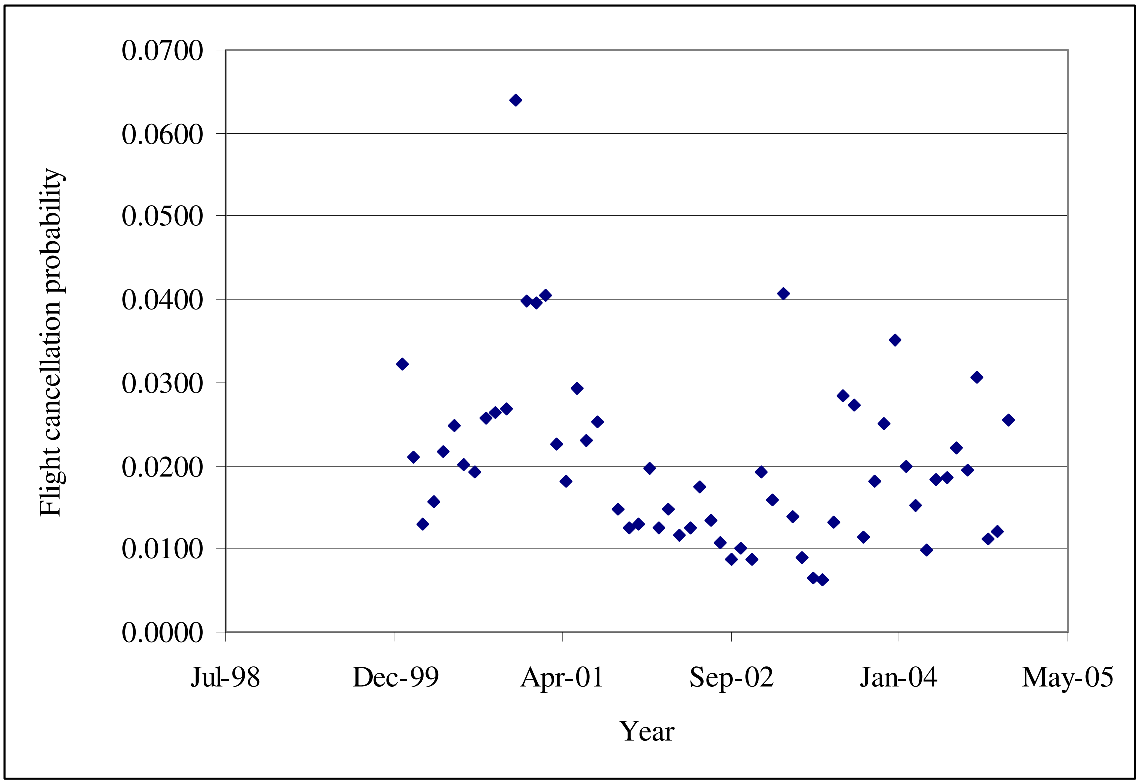


Figure 3 : Flight cancellation probability over the years

2.3.2 Flight Delays

Using the data obtained from ASPM database, the following plot shows the flight delays in the NAS from January 2000 to December 2004. The flight delays had initially decreased but have been on the rise since the beginning of 2003. The delays are computed from the ASPM database for the 35 major OEP airports for each month. It is the average difference between actual gate-in time and the scheduled gate-in time for each flight across all the 35 OEP airports over the entire time horizon (in our case the time horizon is one month). Delays include all flight delays(including those under 15 min) but early arrivals are taken as zero.

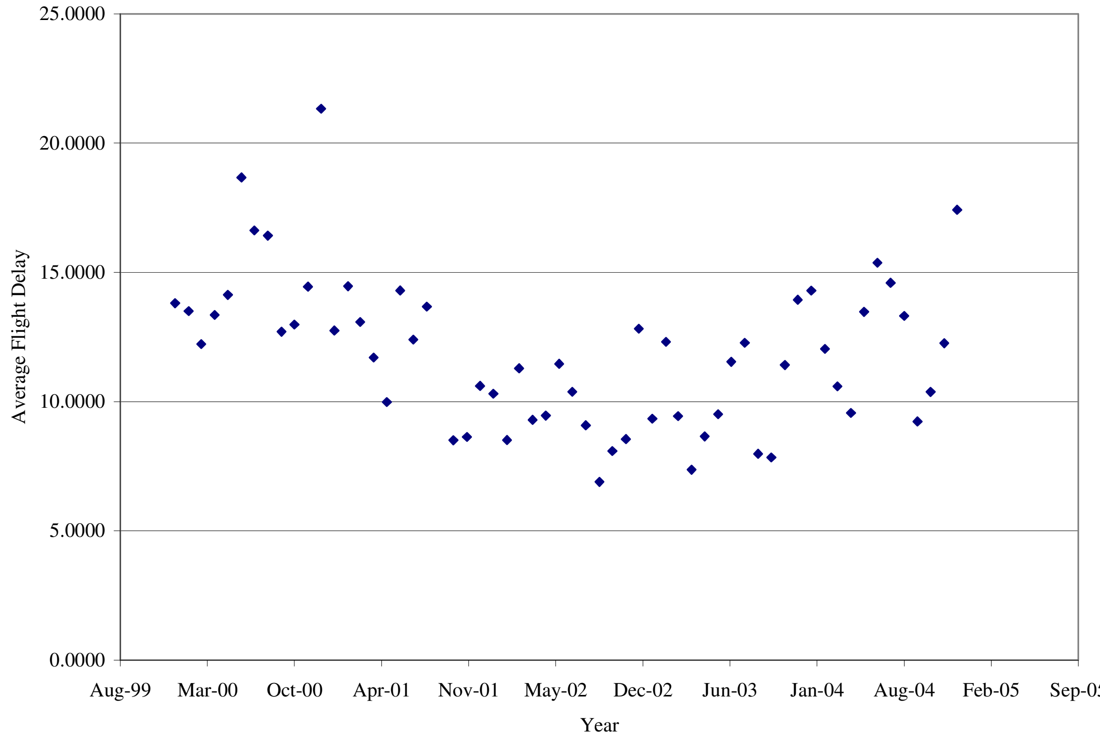


Figure 4 : Flight delays over the years

Chapter 3: MODEL DESCRIPTION

3.1 Overview

In this chapter, the basics underlying our models are described. First of all, the various factors that affect the NAS performance metrics are explored. We will use these factors as the explanatory variables when we formulate the models for flight delays, flight cancellations and passenger delays.

The sources for the data and the methods to process them are described here. The chapter then gives the motivation for the passenger delay metric.

Two different aggregate modeling approaches are used. In the first approach – the whole NAS is considered as a single system and aggregate models are developed. In the second approach, we categorize the airports into discrete categories and develop aggregate models using them.

The following factors will be looked into for modeling:

- Congestion in the National Airspace System
- Load factor of the flights
- Convective en-route weather in the airspace

3.2 Effect of Congestion on NAS performance

Demand has been growing over the years at a much faster rate than the increase in resources. Government organizations (FAA, NASA, local airport authorities) are pursuing measures aimed at redressing congestion over the coming decade. While these measures will significantly help in lowering congestion growth, they will not be sufficient to handle the forecast demand in the next decade. Hence, the need to understand congestion and its impact on the NAS performance becomes significant. Demand has been increasing in the NAS. It can also be seen that the effect of small increase in demands at certain airports has had a severe effect on their delays and cancellations.

Hence, congestion is one important factor that has to be accounted for while modeling flight delays and cancellations. Airport congestion in the future is likely to get worse due to an increase in demand (i.e., low-cost carrier expansion, regional jets, and business aviation) while the supply of airport capacity will likely remain almost constant. Given this clear connection between airport performance characteristics and congestion, we now define a approach where congestion is estimated based on weather conditions (IMC/VMC) and also based on the peak hour demand.

3.2.1 Concept of Rho

The NAS performance models take as input information on NAS capacity and demand and output estimates of NAS performance. The airspace system can be viewed as a queuing system, where customers (flights) arrive at servers (airports) at a mean rate λ and the server processes customers at a mean rate μ. There would be random variations in the actual arrival and service rates leading to the possibility that the server is busy when a customer arrives resulting in the formation of queues. The total time required by a customer is the sum of the time spent in the queue plus the actual service time. For stable queuing systems, rho (ρ) is defined as

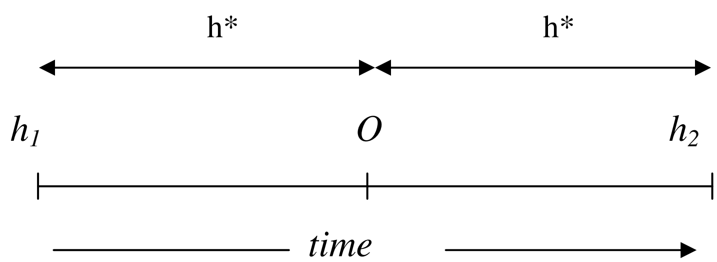
$$\rho = \lambda/\mu = \text{(mean arrival rate) / (mean service rate).}$$

As rho increases, the expected delay experienced by customers becomes very large. Well designed queuing systems typically have rho values that are significantly below unity.

Airports possess limited capacity to handle aircraft arrivals and departures. The capacity, generally measured in operations per hour, depends on basic airport characteristics, including technology available, numbers of runways and runway layout, to name a few. It also varies over time and conditions, based on factors such as weather conditions, runway configuration in use, mix of operations (arrivals vs departures), mix of aircraft types as well as other factors. Also, it depends on whether

Visual Meteorological Conditions (VMC) or Instrument Meteorological Conditions (IMC) exist during the time period in question.

We associate a rho value with any scheduled NAS operation, O. O is any scheduled arrival or departure so that if there are N scheduled flights then there are 2 N operations. Consider the time interval, *I*, that starts at time h^* hours before O (h_1) and ends h^* hours after O(h_2). We calculate the rho value for that interval and associate that value with the operation O.



$$\rho = \left(\frac{\text{\# Operations scheduled during } I \text{ at } O\text{'s airport}}{\text{Capacity(in \# operations) during } I \text{ at } O\text{'s airport}} \right)$$

It is possible for the rho associated with a single operation to be greater than one. This can occur where airlines over-schedule for short periods of time or where adverse weather conditions reduce capacity below what normally would be an acceptable demand level. Our approach is to consider the distribution of rho and then to characterize this distribution by certain statistics – namely the percentile rho-values

- ρ_{50} (the median)
- ρ_{95} and
- ρ_{99}.

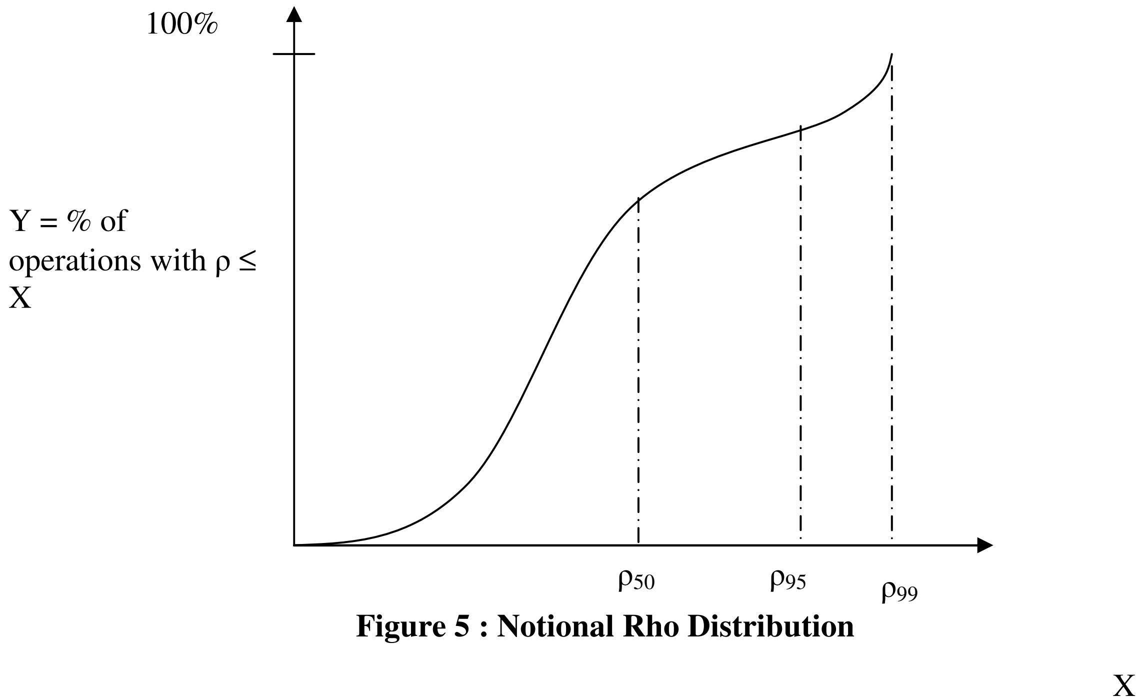


Figure 5 : Notional Rho Distribution

The rho distribution is calculated based on scheduled demand and actual capacity. Key computational approximations in computing Rho is that the airport rho values are computed on an hour-by-hour basis. This means that all operations in a given hour have the same rho value. Rho is defined in terms of the parameter h* as explained above. Flights arriving within 15 minutes of their scheduled arrival time are considered to be on-time. Hence, in that sense h* is 30 min. But for our computation purpose, we have taken h* as one hour and we assume that all operations in that time interval have the same rho value.

3.2.2 Data source and preparation

The data source used is the Aviation System Performance Metrics (ASPM). The following data are used to determine the rho distribution.

- Airport (35 major OEP airports)
- Local Hour (0 to 23 hours)
- Scheduled Departures (total number of scheduled departures)
- Scheduled Arrivals (total number of scheduled arrivals)
- Average Gate Arrival Delay (actual gate arrival delay-including flights that arrive within 15 minutes of scheduled arrival time)
- Cancelled flights (total number of cancelled flights)
- Airport Arrival Rate(AAR) (as reported in ASPM–accounts for VMC/IMC)
- Airport Departure Rate(ADR) (as reported in ASPM–accounts for VMC/IMC)

We will now describe the algorithm for estimating Rho 50, Rho 95 and Rho 99.

RHO50 is the median of the distribution of RHO(O) over all operations, O, in the NAS.

RHO95 is the 95^{th} percentile of the distribution of RHO(O)

RHO95 is the 99^{th} percentile of the distribution of RHO(O)

Using the above data, we compute a histogram RHO_HIST(A) where for each hour we compute the following

Rho = (Scheduled Arrivals + Scheduled Departures)/(AAR + ADR)

Now, compute

$RHO\_NAS(J) = \Sigma_{\text{all airport classes A}}\ P\_OPS(A) * RHO\_HIST(A,J)$ for J = 1, …,24

where

P_OPS(A) = the percent of NAS operations associated with airport A

RHO_HIST(A,J) = the probability that the RHO(O) = J * .1 for an operation O within the airport A. The rho for each hour in each airport is computed and a histogram is made. The histogram gives the number of operations that happen in the time interval for the given demand/capacity ratio. It is the rho distribution of each hour for the airport.

When the actual rho is computed, it takes into account the scheduled operations and actual capacity. Hence, this accounts for the VMC and IMC conditions that might exist in a given hour. If IMC condition exist, the capacity goes down in most of the airports and hence the rho for that particular hour increases when compared to a similar demand devel with VMC conditions. This would be the approach to measure the impact of weather conditions on the performance metrics.

Once the histogram for the whole NAS is obtained, the median of the operations is taken as Rho50. Similarly Rho95 and Rho99 can be determined analytically.

3.3 Load Factor

Load factor is the total percentage of available seats filled in a flight. Figure 6 shows the variation of load factor over the years. We can observe that the load factor has been increasing significantly over the years. From Figure 7, we can see some negative correlation between load factor and cancellation probability. This can be explained by a reluctance on the part of airlines to cancel flights if there is little or no space on subsequent flights to assign disrupted passengers.

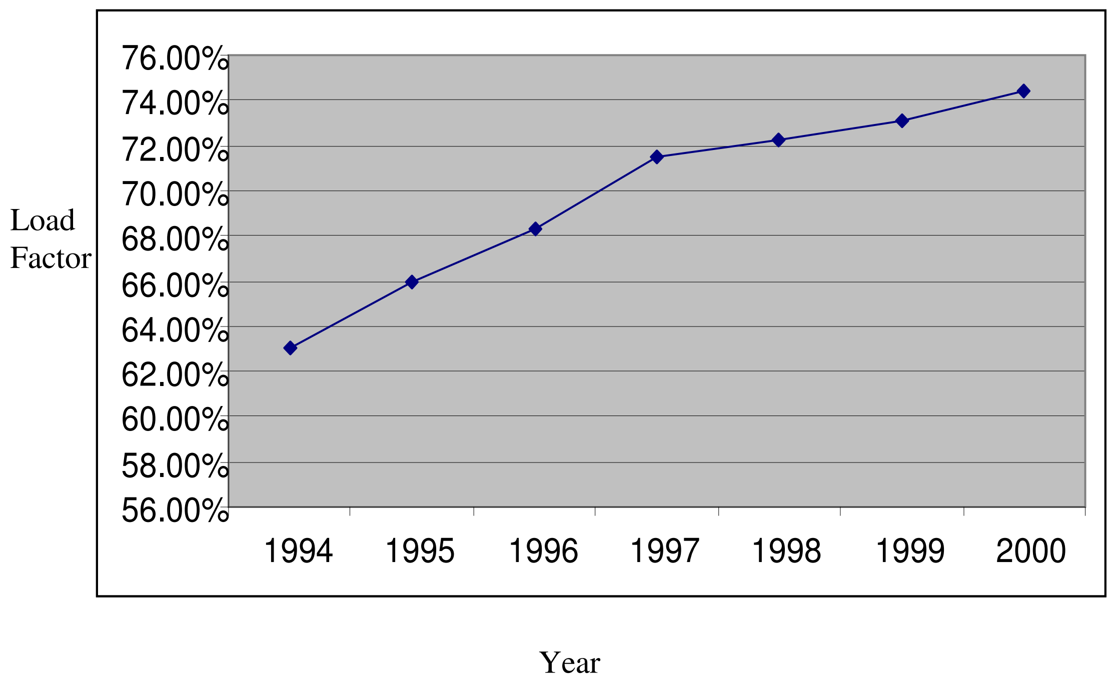


Figure 6 : Load factor over the years

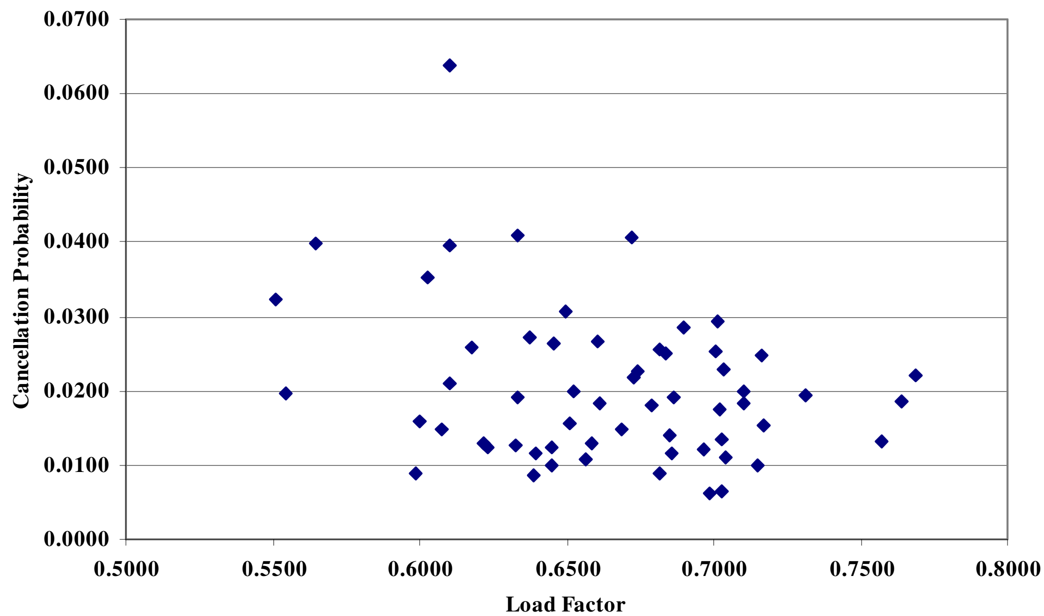


Figure 7 : Load factor against cancellation probability

3.3.1 Data source and preparation

We define load factor for a flight as

Load Factor = (Total passengers boarded) / (Total available seating capacity)

The Bureau of Transportation Statistics(BTS) provides a 10% sample of coupons(tickets) obtained from the airlines. This is called the T-100 database where for all the major airports, the total available seating capacity and total passenger flown are reported. Using this data, we computed the average load factor of flights for the NAS.

3.4 Convective Weather

Flights undergo delays(both enroute and ground delays) because of Traffic flow management initiatives in response to weather conditions and excessive traffic volume. Weather has been identified as the most important causal factor for NAS delays. Hence, there is a need to come up with a metric that accounts for convective weather. When rho is computed, terminal area weather (ceiling/visibility) is already taken into account since capacity is computed based on VMC/IMC values. Thus, this part of weather is already handled. But what is needed is something that capture enroute weather. Enroute weather impacts both delays and cancellations. FAA initiatives like ground delay programs, flow constrained areas, etc impact flights flying through the weather affected area. The flight maybe subjected to ground delays, rerouting (incurring additional delay) or cancellation.

3.4.1 Weather Impacted Traffic Index

A generic definition of the Weather Impacted Traffic Index (WITI) is the number of aircraft affected by the weather at a given instant of time. Computation of WITI was performed using extended regions around severe weather cells, and a set of statistical features, histogram based features, and time-domain features of WITI time histories were used to establish the best correlation between the estimated and the reported NAS delays. Many such WITI's have been developed using various approaches. An exhaustive modeling of WITI is only available over a limited time horizon.

3.4.2 Weather Index based on lightning strike data

Considering that WITI has been difficult to compute and obtain for a large dataset, we used a weather index based on lightning strike data developed by the FAA. The above figure shows the various lightning strike points in a given month. The lightning strike based convective weather index is created by finding where the scheduled flight plans intersect actual lightning strikes in a latitude/longitude and time based grid. This is computed from the ETMS flight plans.

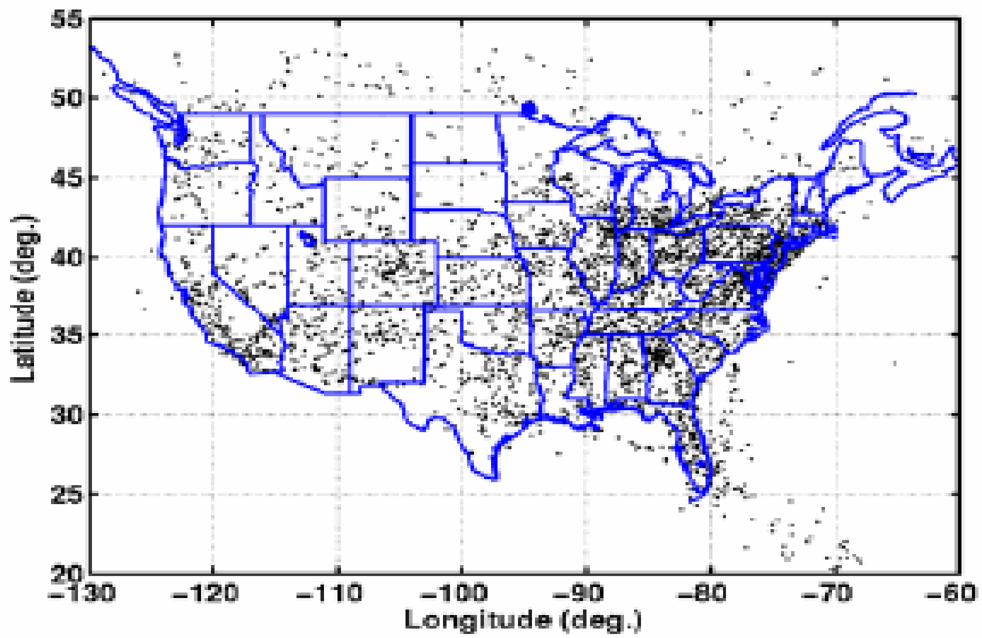


Figure 8 : Lightning strikes in NAS

The index is determined by the intensity of the lightning strike and the number of flights in the grid center. The cell size is the size of a sector. For each lightning strike, the demand that would have flown across that sector in that time period (15 minutes about the lightning strike) as per the scheduled flight plan is computed.

3.5 Passenger Delay Analysis

Considering that the airline industry is a highly competitive business, service reliability serves as a major advantage to attract and retain passengers. Hence, on-time performance metrics of passengers constitute a very important role in decision making and in profits. While longer block times can improve on-time performance, they result in greater operating costs for the airlines. Here, we try to estimate passenger delay in order to measure passenger schedule reliability. No actual measure of passenger delay metric is publicly available. All the passenger delay information are proprietary and no data on passenger delay is available.

Some of the factors that affect passenger delays are :

- Distribution of flight delays
- Flight cancellation rate
- Average Load factor
- Percentage of passengers with 2 or more flight legs in their itinerary

We explain in detail the methodology we will follow in computing passenger delay metric.

3.5.1 Scenario tree

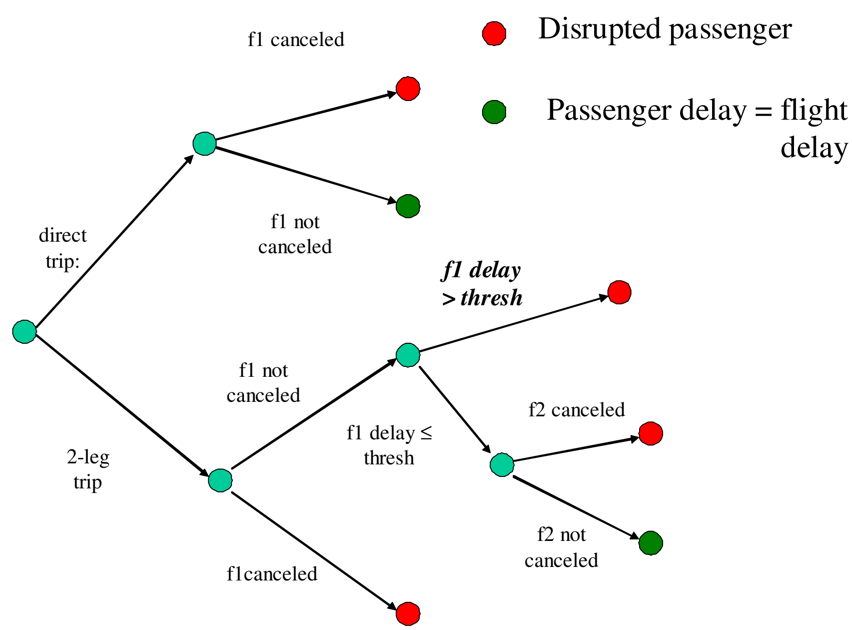


Figure 9 : Scenario tree to estimate passenger delay

We construct the above scenario tree to estimate passenger delay. The scenario tree captures all factors through which a passenger can get delayed. We assume that all flights are either 1-leg or 2-leg trips. The number of 3 or more leg trips is very minimal and hence these are not included. The diagram enumerates the various events that could occur on a 1 or 2 leg passenger itinerary, where for a 1-leg trip, the flight is denote by *f1* and for a 2-leg trip the first flight is *f1* and the second is *f2*. Each of these leads to a different passenger delay. An example of passenger delay calculations is given in appendix 3 based on this state enumeration approach.

The various possibilities that could arise are as follows:

- The passenger takes 1-leg trip.
    a. His delay is the delay of the flight.
    b. If the flight is cancelled, the passenger is disrupted.
- The passenger takes 2-leg trip.
    a. The first flight gets cancelled. The passenger is disrupted.
    b. The first flight arrives late
        i. The flight is not late enough for the passenger to miss the connecting flight
        ii. The flight is delayed sufficiently so that the passenger misses the connecting flight. The passenger is disrupted.
    c. The first flight arrives before second leg is scheduled to depart
        i. The second flight is canceled. The passenger is disrupted.
        ii. The second flight takes off and the passenger delay is the delay of the second flight.

A key calculation required to estimate passenger delay is the probability of a missed connection.

Let D(f) be the random flight delay. (actual flight delays – delays of flights that arrive within 15 minutes of scheduled arrival time are also taken as the actual delay time)

D_m be the mean flight delay (flights that are delayed more than 15 minutes)

P_{MISS} is the probability of a passenger missing a connection that we need to compute. This is an approximate method to compute the probability of passenger missing a connecting flight. This is estimated only statistically and we do not have an extensive data on all the parameters to validate the model.

We define two terms :

- LAY : average flight layover for connecting flights..
- CONNECT : minimum time required to connect between two flights

Given the above, we the probability that a connection is missed because of a delayed flight:

$$P_{MISS} = \text{Prob}\{D(f) > \text{LAY} - \text{CONNECT}\}$$

We assume that if the flight is delayed less than 15 mintues, then passenger makes the connection.

The following are estimated to determine D(f) :

P_{DELAY} = the probability that a flight's delay > 0 Thus, we can partition flights into two sets: the on-time flights and the late flights (delay > 15 minutes).

P_{DELAY} is the probability that a flight is late.

Hence, the mean delay of late flights, $D_{m\text{-}late}$ by

$$D_{m\text{-}late} = D_m / P_{DELAY}.$$

Given this, we model D(f) and that is used to compute P_{MISS}

Section 4.4.2 explains how statistically D_m is estimated. In section 4.4.3, D(f) is estimated. While estimating D(f), we condition it based on D_m. For given average flight delays (where flight delays are computed for flights delayed >=15 min), D(f) gives the distribution of flights arriving with various levels of delay.

3.5.2 Disrupted passenger

In the above section, we described scenarios when a passenger's itinerary is disrupted

- The flight is cancelled (either the first leg or second leg)
- The first flight is late so that the passenger misses the connecting flight

The disrupted passenger undergoes more delay because his recovery time can never be guaranteed. He might be able to get onto the next flight or might have to stay overnight to get the next available flight. We use a single delay value for a disrupted passenger. This is certainly an area where better modeling would be useful.

3.6 Categorizing Airports

While the previous section considered the NAS as one single system, such an approach has its own limitations. We cannot distinguish between low density airports and highly congested airports. Hence, the model is not flexible enough with respect to demand changes. Having all airports in the model is not feasible. Hence, we introduce the concept of categorizing airports. We will have minimal number of categories so that we retain the aggregate approach but still have enough flexibility to perform scenario-change analysis.

3.6.1 Factors used to categorize airport

Airports are classified into different categories based on the following parameters:

- (daily demand) / (daily capacity)
- F-BUSY(A) = fraction of traffic during busy period for airport A
- W-BUSY(A) = width of busy period for airport A

  We assume that F-BUSY(A) >= W-BUSY(A).
- IMC-FRACT(A) = (IMC capacity of airport A) /(VMC capacity of airport A)
- IMC-TIME(A) = fraction of busy period that airport A experiences IMC.
- Congestion metric, which is defined as follows

$$\text{Congestion Metric} = p1 * (D_I/IMC) + p2*(D_V/VMC)$$

p1 and p2 are the probabilities of occurrence of IMC and VMC conditions, respectively.

D_I and D_V are the number of scheduled operations during IMC and VMC periods, respectively.

IMC and VMC are the IMC and VMC capacities, respectively.

Using the above parameters, we categorize airports into the following classes:

- ✓ High Demand/Capacity, high IMC/VMC
- ✓ High Demand/Capacity, medium IMC/VMC
- ✓ High Demand/Capacity, low IMC/VMC
- ✓ Medium Demand/Capacity, high IMC/VMC
- ✓ Medium Demand/Capacity, medium IMC/VMC
- ✓ Medium Demand/Capacity, low IMC/VMC
- ✓ Low Demand/Capacity

Airport cluster characteristics are fixed – so airports can move among classes over time. The IMC/VMC ratio is based on two quantities – the ratio of the capacities and the ratio of time for which IMC exists. Hence, an airport which has high IMC/VMC but does not experience IMC conditions that often would not be categorized under high IMC/VMC.

Chapter 4: Model Results and Validation

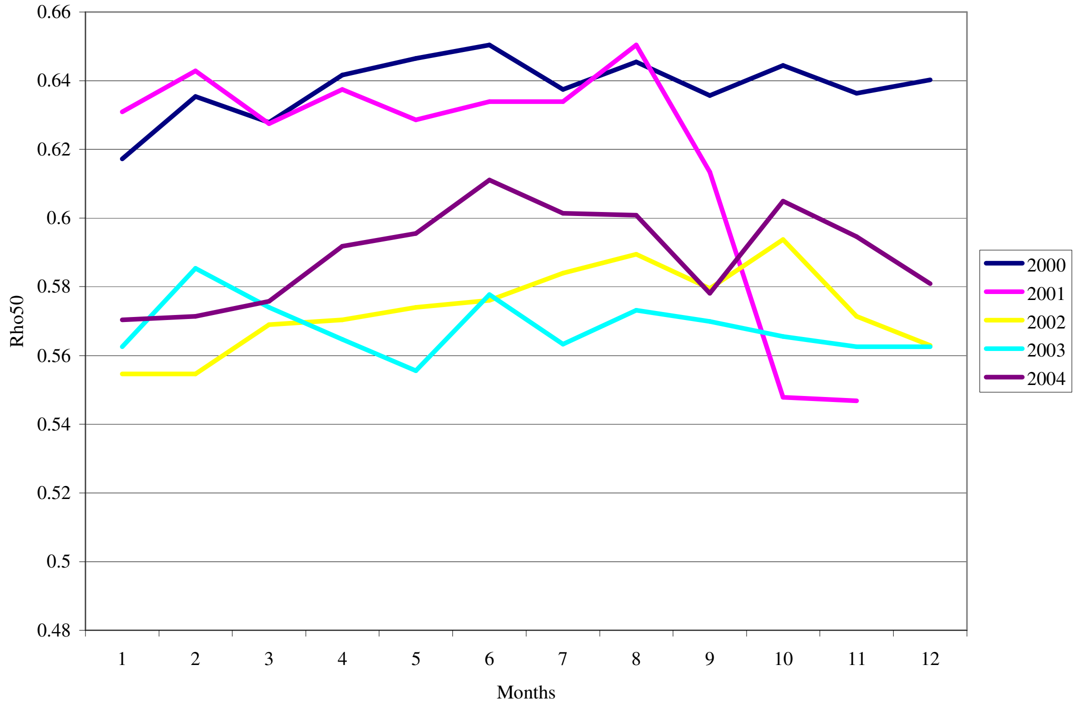
4.1 Overview

In this chapter, our performance metrics are modeled using statistical techniques. The variables described in Chapter 3 are used to model the three performance metrics.

First, the modeling framework used for calibration with historical data will be described. Then, our modeling assumptions are discussed in further detail. Next, the parameters underlying the to flight delay and cancellation models and procedure used for the modeling techniques are explained. The flight delay and cancellation models using airport categories are explained next. The validations of these models are then presented. Passenger delay is then modeled using the flight delay and cancellation models.

4.2 Calibration of Monthly Models for NAS

From the ASPM database, we compute Rho 50, Rho 95 and Rho 99 for each month for the NAS. The following plot shows the monthly variation of Rho 50 and Rho 95 from January 2000 to December 2004.



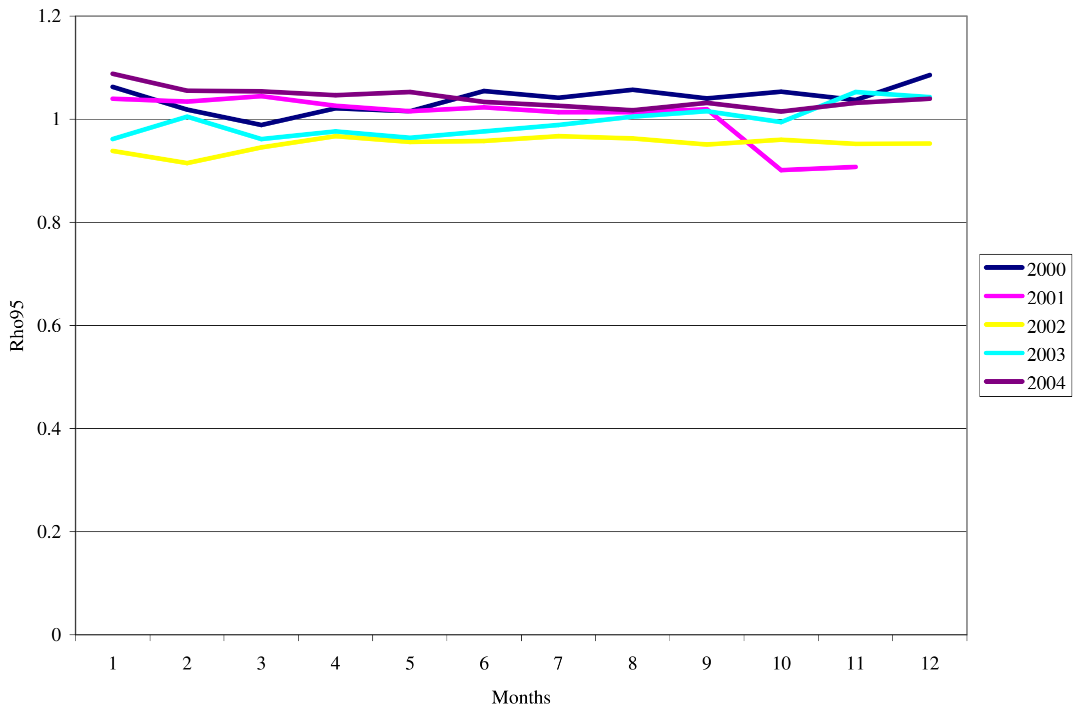


Figure 10 : Rho 50 and Rho 95 over the years

NAS Rho50 and Rho95 are the 50th and 95th percentile of scheduled operations in NAS respectively.

4.2.1 Flight Cancellations

The following plot shows the variation of flight cancellations with Rho 50 and Rho 95.

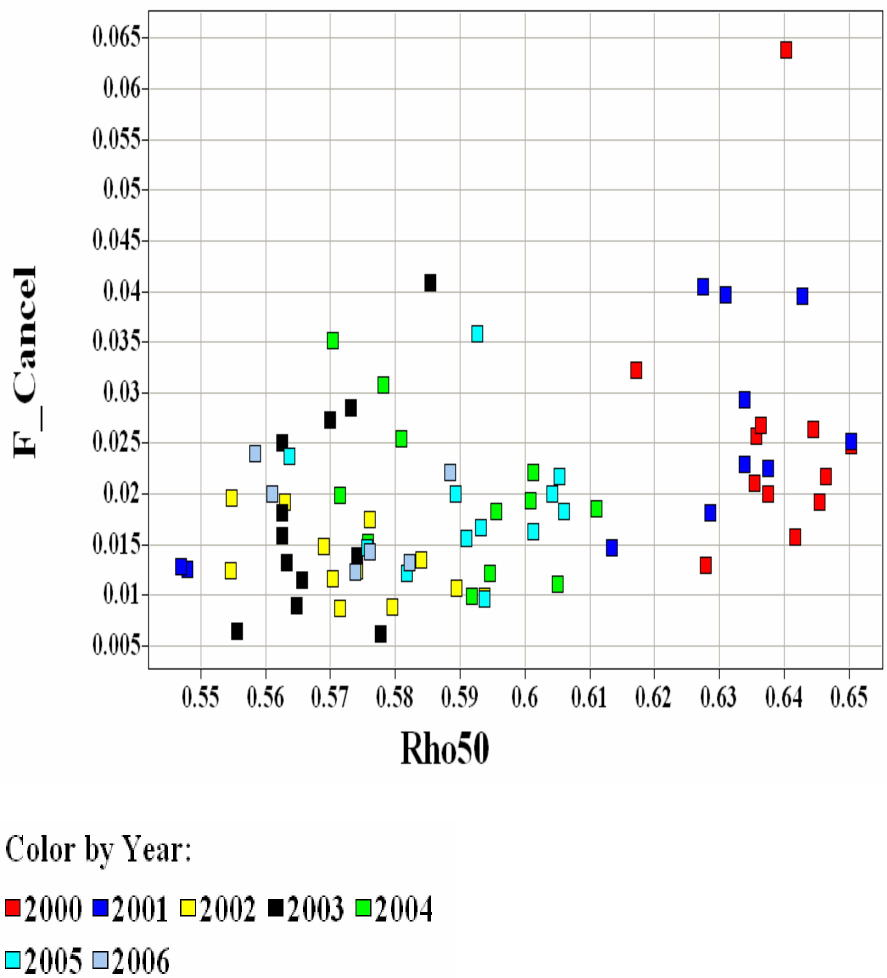


Figure 11 : Flight cancellation against Rho 50 over the years

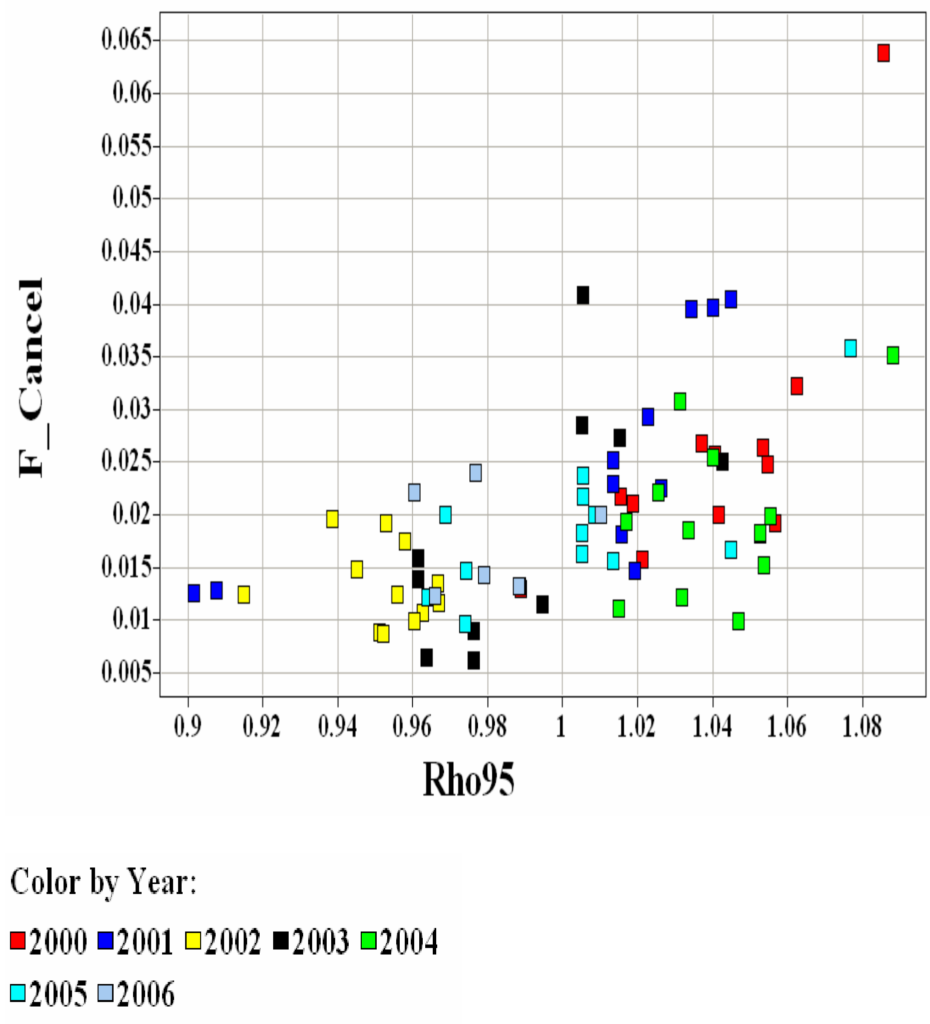


Figure 12 : Flight cancellation against Rho 95 over the years

As Rho50 increases, tendency to cancel flights increases. Rho50 gives an early indication of the severity of the congestion. At high values of Rho95, NAS is very congested and a decision to cancel flights will be too late (considering high passenger handling expenses – as there will be very less other re-scheduling options). Hence, a better sense of the probability of cancellation can be obtained using Rho50 rather than Rho95. Also, the model obtained here using the data fitted using Rho50 yielded better results than Rho95. Considering these, we use Rho50 as an independent variable in our model. Also, as detailed in Section 3.3, load factor plays a very significant role while a decision to cancel a flight is taken. Hence, Rho50 and load factor are used while estimating the model for probability of cancellation of flight for NAS.

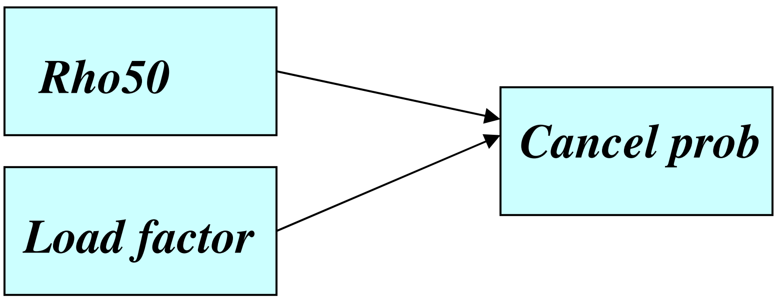


Figure 13 : Factors involved in Probability of Cancellation

Having all the necessary input(rho50 and load factor), we do a regression for various functional forms of the dependent and independent variables.

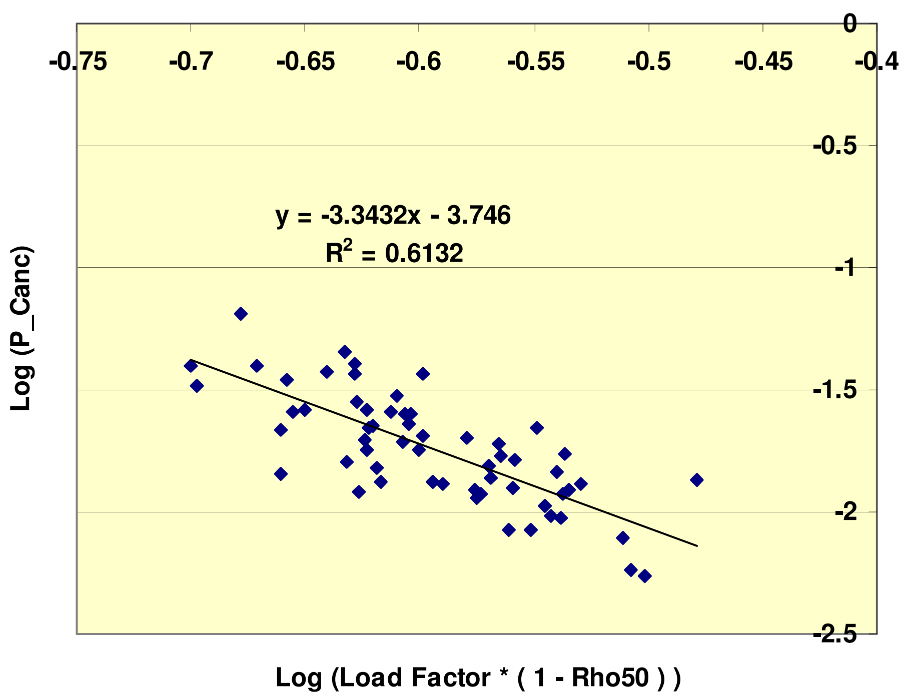


Figure 14 : Computing Probability of Cancellation

The various functional forms tried were : linear form ($a=b^x+c$ form), power series ($b=ax$ form), polynomial series form($a= bx^2+cx+d$ form) and logarithmic form. The functional forms were used for either or both the dependent independent variables. The following model was selected as it yielded the highest R^2 value of 0.6132.

$$\textbf{F\_Cancel} = e^{-3.75} * [\ \textbf{Loadfactor} * (\ 1 - \textbf{Rho50})\ ]^{-3.34}$$

4.2.2 Flight Delays

The following plot shows the variation of flight delays with Rho 50 and Rho 95.

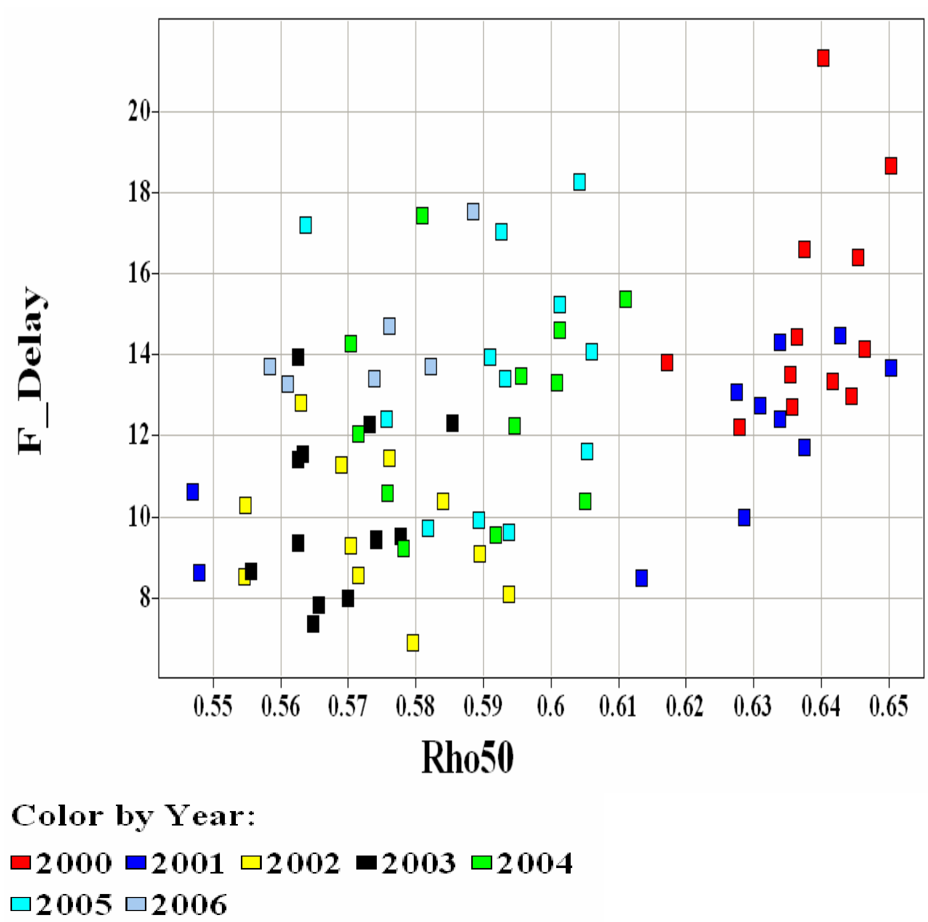


Figure 15 : Rho 50 against Flight delays over the years

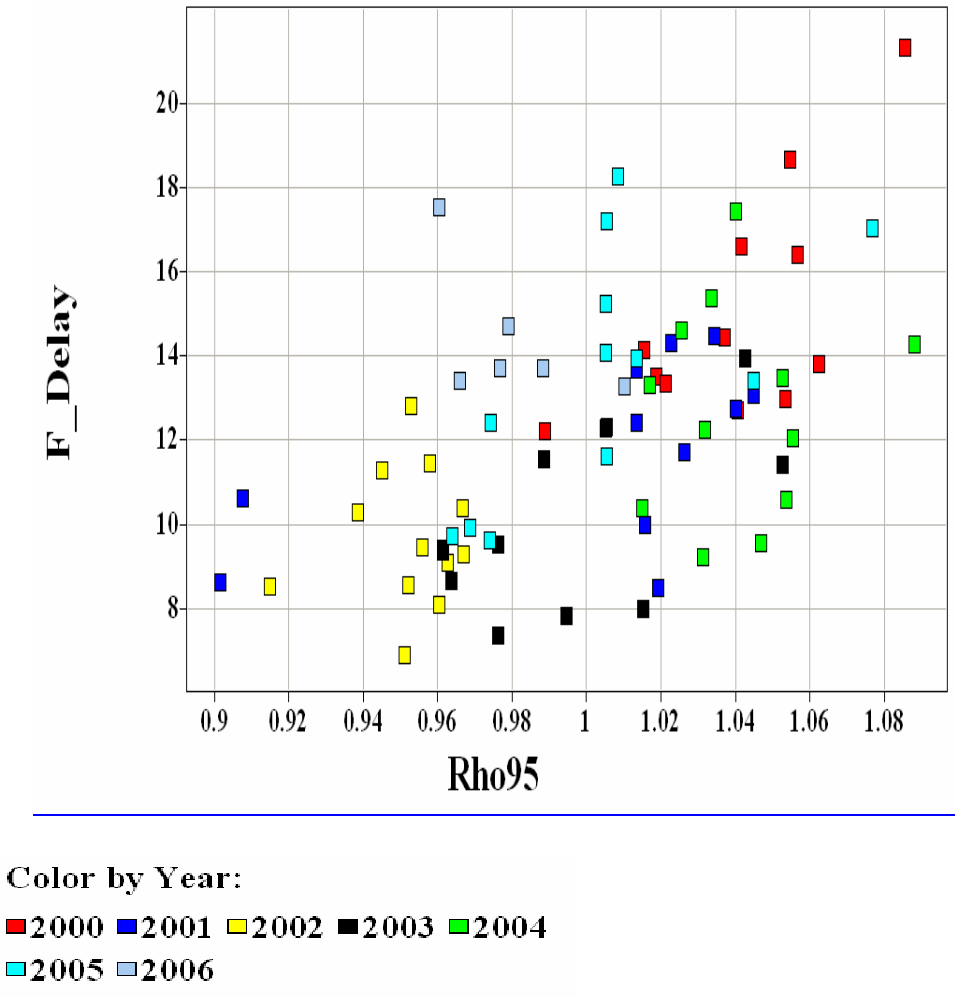


Figure 16 : Rho 95 against Flight delays over the years

We used Rho95 and the probability of cancellation to calibrate the model for average delay. Similar to the cancellation model, various functional forms for both the dependent and independent variables were tried and the following model was chosen as it yielded the highest R^2 value of 0.6862.

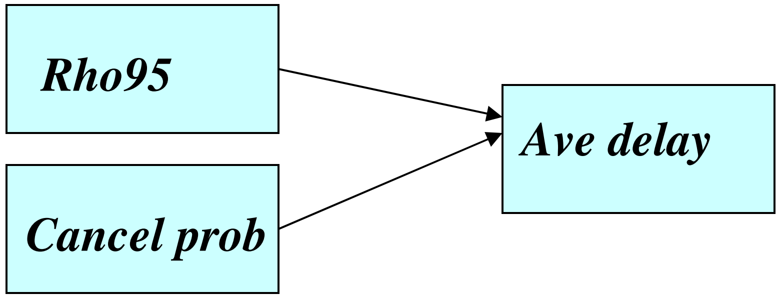


Figure 17 : Factors involved in average flight delay

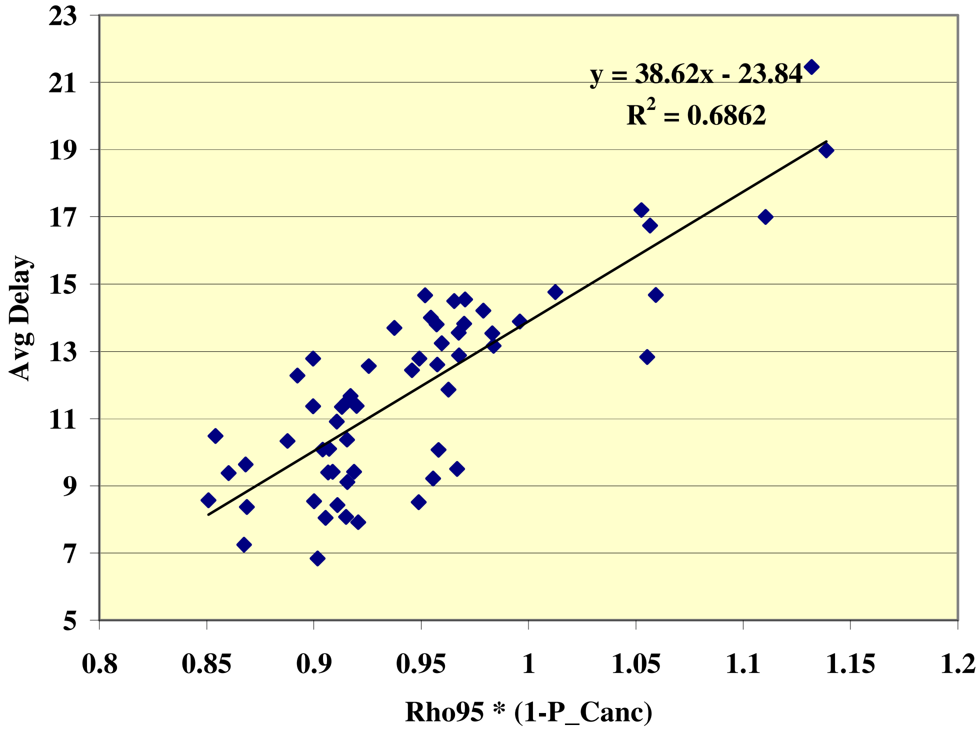


Figure 18 : Computing average flight delay

F_Delay = 38.62 * [Rho95 (1 – F_Cancel)] – 23.84

4.3 Calibration of Monthly Models using Airport Categories

4.3.1 Airport Categories

The models developed in section 4.2 consider the NAS as a single system and hence cannot easily respond to specific changes in airport characteristics. As explained in Section 3.6.1, we categorize the NAS airports. From ASPM data, for the 35 OEP airports, the categorizing parameters are either obtained or computed. The 7 airport categories are

a. High Demand/Capacity, high IMC/VMC
b. High Demand/Capacity, medium IMC/VMC
c. High Demand/Capacity, low IMC/VMC
d. Medium Demand/Capacity, high IMC/VMC
e. Medium Demand/Capacity, medium IMC/VMC
f. Medium Demand/Capacity, low IMC/VMC
g. Low Demand/Capacity

The following methodology is used to categorize airport

The demand/capacity ratio is computed for each airport and based on the following values, they are categorized either as high, medium or low demand/capacity airports.

- If $1 < \text{Demand/Capacity} > 0.7$ it is categorized as High
- If $0.4 < \text{Demand/Capacity} < 0.7$, it is categorized as medium
- If $0 < \text{Demand/Capacity} < 0.4$, it is categorized as low.

The breakpoints were chosen so that there are enough airports in each of the three categories. Various combinations for the breakpoints were tried until the breakpoints are chosen so that each category has enough airports so as to perform further analysis. This is another area where a more robust statistical method can be used for categorizing the airport based on their demand and capacity.

If the congestion metric for a particular hour is greater than 0.6, that hour is considered as a busy hour. The congestion metric was also chosen so that there are sufficient hours in the congested-hour metric. Peak hour values were one major factor while determining the congestion metric's threshold. The breakpoint was to ensure that peak hours are included in the busy-hour metric and that traffic in most of the airports in all the busy hours included is very much greater than traffic at other time intervals.

Each airport is categorized into appropriate clusters based on the following basis:

a. Compute demand/capacity and classify the airport has high,medium or low.
b. Compute busy period width and traffic in busy period. Traffic above 0.6 is considered high, between 0.5 and 0.6 is considered medium and below 0.5 is considered low. Similarly, for busy period, the congestion metric has to be above 0.6.
c. Compute IMC/VMC capacity and period of time for which it exists. If IMC/VMC is greater than 0.85, it is considered high, between 0.85 and 0.75 is considered as medium and below 0.75 is considered low.

Using the above criteria, all airports will fall into one of the 7 categories. When the demand is low, we do not check for the conditions (b) and (c).

Rho distribution is computed for each of the airport classes. Computing rho distribution for each airport class is exactly the same as how we determine for NAS – the only difference being that while for NAS we take into account all the 35 major airports while for each category, we just take in those airports that are categorized under them. Hence, given the airport list, we compute the hourly demand/capacity for each of the airports in that list and determine the 50^{th}, 95^{th} and 99^{th} percentile of operations (as explained in section 3.2)

Each category with its list of airports are given in the following table

	Category g	Category f	Category e	Category d	Category c	Category b	Category a
2000	TPA	IAH	PDX	MDW	IAD	JFK	ATL
	MCO	STL	MIA	PHX	DTW	PHL	ORD
	SLC	DCA	CLT	SEA	SFO	DFW	LGA
	BWI	LAS	FLL	DEN	LAX	EWR	BOS
			SAN	MSP			
				CVG			
2001	TPA	LAS	PDX	MDW	IAD	PHL	ATL
	MCO	SAN	MIA	PHX	DTW	DFW	ORD
	SLC	IAH	CLT	SEA	JFK	EWR	LGA
	BWI		FLL	MSP	LAX	DEN	BOS
	STL		DCA	CVG	SFO		
2002	TPA	LAS	PDX	MDW	IAD	JFK	ATL
	MCO	IAH	MIA	PHX	DTW	PHL	ORD
	SLC	BWI	CLT	SEA	LAX	DFW	LGA
	SAN		FLL	DEN	SFO	EWR	BOS
	STL		DCA	MSP			
			CVG				
2003	TPA	MIA	PDX	CVG	IAD	JFK	ATL
	MCO	SAN	SEA	MDW	DTW	DFW	ORD
	SLC	IAH	CLT	PHX	PHL	EWR	LGA
	BWI	LAS	FLL	MSP	SFO	LAX	BOS
		STL	DCA	DEN			
2004	TPA	MIA	PDX	IAH	IAD	LAX	ATL
	MCO	STL	CVG	MDW	DTW	PHL	ORD
	SLC	LAS	CLT	PHX	JFK	DFW	LGA
	BWI	SEA	FLL	MSP	DCA	EWR	BOS
	SAN			DEN	SFO		
2005	TPA	CVG	PDX		IAD	JFK	ATL
	MCO	SAN	MIA	MDW	DTW	PHL	ORD
	SLC	IAH	CLT	PHX	DEN	DFW	LGA
	STL	BWI	FLL	SEA	LAX	EWR	BOS
			LAS	MSP	DCA		
					SFO		
2006	TPA	CVG	PDX	MDW	IAD	JFK	ATL
	MCO	STL	MIA	PHX	DTW	PHL	ORD
	SLC	BWI	CLT	MSP	LAX	DFW	LGA
	SAN	SEA	FLL	DEN	DCA	EWR	BOS
		LAS	IAH		SFO		

An example of categorizing a particular airport is given below :

For the year 2004, we take LAX.

The average demand/capacity = 0.73. Hence, the airport is a high demand/capacity airport. Hence, it will be in one of the three categories – a, b or c. (These are high demand/capacity categories – depending on other parameters, the right category will be chosen).

The congestion metric is computed and the width of busy hour is computed as 0.25

Fraction of traffic in busy hour = 0.52

The ratio of the capacities : IMC/VMC = 0.83

Amount of time for which IMC conditions existed = 8%.

Hence, the airport is highly congested, but does not have volume of traffic in congested hours and also high IMC/VMC ratio. Hence, it is classified as category b.

4.3.2 Flight Cancellations

The cancellation model described in 4.2.1 considers NAS as a single system. As outlined in the previous section, we would want a model that would change to specific changes in airport characteristics. That motivated us to categorize airports. Hence, we would want a model that would have a structure that would enable us to change some of the key parameters. We have estimated a model that gives the option to change the congestion metrics (Rho distribution) for each of the airport categories, load factor of NAS and the weather index of NAS. The probability of cancellation is computed as a function of Rho 50, Rho 95, Rho 99, load factor and weather index.

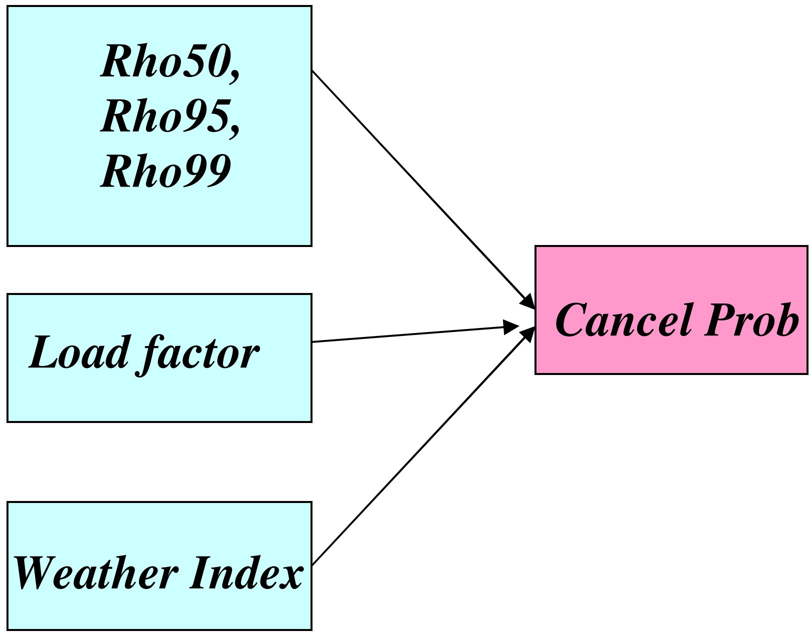


Figure 19 : Probability of cancellation using airport clusters

The functional form is

NAS Cnx = f($\mathbf{Rho50_i}$,$\mathbf{Rho95_i}$,$\mathbf{Rho99_i}$,Loadfactor,W-Indx)

where *i* represents values for each of the individual airport classes

Functional form :

$$
\begin{aligned}
\text{Cnx} &\\
&= \sum (a_{i1}\text{Rho50}_i(1\text{-LF})\text{^}b_{i1} \;+\\
&\quad a_{i2}\text{Rho95}_i(1\text{-LF})\text{^}b_{i2} \;+\\
&\quad a_{i3}\text{Rho99}_i(1\text{-LF})\text{^}b_{i3}\,) +\\
&\quad c(\text{WITI})
\end{aligned}
$$

i=1 to 7 (represents the 7 different airport classes)

WITI is the weather index for NAS

A regression was performed and the model has $R^2 = 0.7081$

The cancellation model results are given in the appendix A.

4.3.3 Flight Delays

The average flight delay is computed as a function of Rho 50, Rho 95, Rho 99, load factor and cancellation probability.

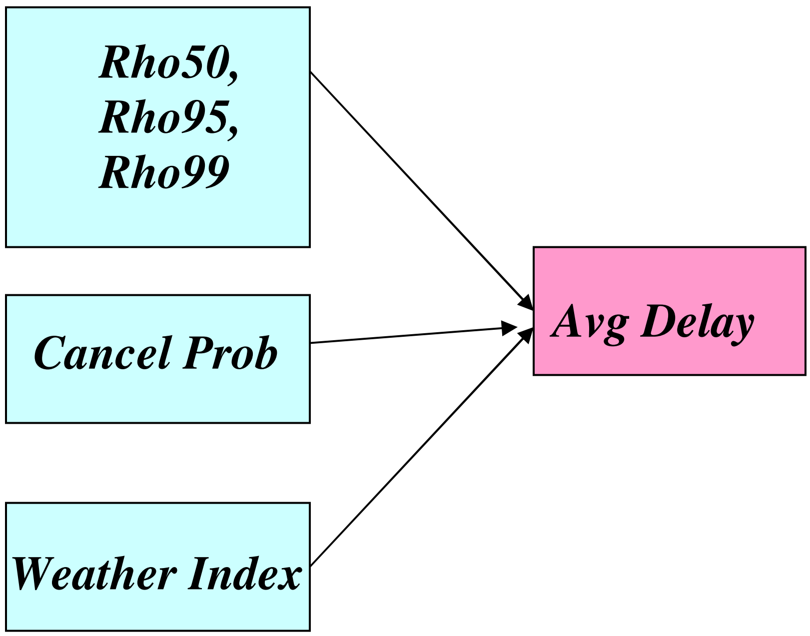


Figure 20 : Average flight delays using airport clusters

The functional form is

NAS Delay = f($Rho50_i$,$Rho95_i$,$Rho99_i$,Loadfactor,Cnx)

where *i* represents values for each of the individual airport classes

Functional form :

Delay

$$= \sum (a_{i1} Rho50_i (1-Cnx)^{\wedge} b_{i1} + a_{i2} Rho95_i (1-Cnx)^{\wedge} b_{i2} + a_{i3} Rho99_i (1-Cnx)^{\wedge} b_{i3}) + c(WITI)$$

i=1 to 7 (represents the 7 different airport classes)

WITI is the weather index for NAS

A regression was performed and the model produced an $R^2 = 0.7212$

The model model results are given in the Appendix B.

4.4 Passenger Delay

Having obtained the models for flight delays and cancellation rate, we now move on to estimate the average passenger delay. As outlined in section 3.5, we first estimate all the necessary parameters required and finally determine the passenger delay. From the scenario tree for the passenger delay model, we compute passenger delay using the following formula :

P_DELAY =

F_DIRECT/100 * (1 – F_CANCEL/100) * F_DELAY
+
F_DIRECT/100 * F_CANCEL/100 * P_DEL_DISRUPT
+
(1 – F_DIRECT/100) * F_CANCEL/100 * P_DEL_DISRUPT
+
(1 – F_DIRECT/100) * (1 - F_CANCEL/100) * (1 - F_CANCEL/100) * (1 - P_MISS) * F_DELAY
+
(1 – F_DIRECT/100) * (1 - F_CANCEL/100) * (1 - F_CANCEL/100) * (P_MISS) * P_DEL_DISRUPT
+
(1 – F_DIRECT/100) * (1 - F_CANCEL/100) * F_CANCEL/100 *P_DEL_DISRUPT

The output of the model is :

P_DELAY : Average Passenger Delay

The inputs are :

F_DIRECT : Proportion of people taking direct flight

F_CANCEL : Probability of flight getting cancelled

F_DELAY : Average flight delay

P_DEL_DISRUPT : Average delay of disrupted passengers

P_MISS : Probability that a passenger misses connecting flight

From BTS data, we obtained an estimate that two-third of the passengers take direct flight. ie., we set

F_DIRECT = 0.66,

in our model. The data was taken from the 10% ticket sample data in BTS. The time period chosen was from January 2000 to December 2004.

There are no publicly available data giving delay statistics for disrupted passengers. Disrputed passengers must be re-assigned to a later flight and often experience overnight stays. From an MIT simulation based on actual proprietary data, we use an estimate of 420 minutes as the average delay of disrupted passengers [5].

P_DEL_DISRUPT = 420 min

The values for F_CANCEL and F_DELAY can be obtained from one of the cancellation and delay models described earlier. For passengers taking flights that take-off as per schedule, their delay is the delay of the flight. The model should also use the probability of a passenger who is scheduled to fly on a flight that is canceled. This is slightly different from the probability that a flight is canceled. When flight cancellations are considered, it doesn't take into account the number of seats it has and the number of passengers that were scheduled to fly in that flight. And one cancelled flight does not translate into one passenger (or a linear number of passengers) being cancelled. The disrupted passengers are those who are in the cancelled flights. Since we do not have actual passenger data for each of the cancelled flights, we use the flight cancellation probability, which is an approximation of the probability that a passenger is scheduled to fly on a flight that is cancelled.

The following section describes how the probability of a passenger missing a connecting flight is computed.

4.4.1 Probability of passenger missing connecting flight

As explained in chapter 3, in a 2-leg trip, whenever the first flight in a two-leg itinerary is sufficiently delayed the passenger misses the connecting flight and the passenger is disrupted. In this section, we present a model for estimating the probability of a passenger missing a connecting flight on a two-leg itinerary.

We model the probability of passenger missing connecting flight as a conditional probability. Specifically, we assume that if a flight is not classified as delayed by the

FAA 15 minute delay criterion, then the passenger makes the connection to the second flight leg. Thus, we estimated the probability that the connection is missed given that the flight is delayed. Furthermore, we wish to estimate this conditional distribution as a function of the average flight delay. In this way, we can estimate passenger delay as a function of flight delay. Thus, we will estimate the flight delay distribution conditioned on

1) Flight delay > 15 minutes and
2) Overall average flight delay = D , for select constants D

Hence, as a first step we determine how many flights are delayed more than 15 minutes in a given month. To estimate the probability of missing a connecting flight, we start by determining the delay distribution of the flights.

Once we have the probability of a flight getting delayed and the distribution of flight delays, the probability of passenger missing connecting flight is computed. Each flight has a layover time and each passenger requires a minimum connection time to catch the connecting flight successfully. A passenger takes the connecting flight if the delay of the first flight <= (Layover time – Connection Time)

This whole procedure can be explained in the following flowchart :

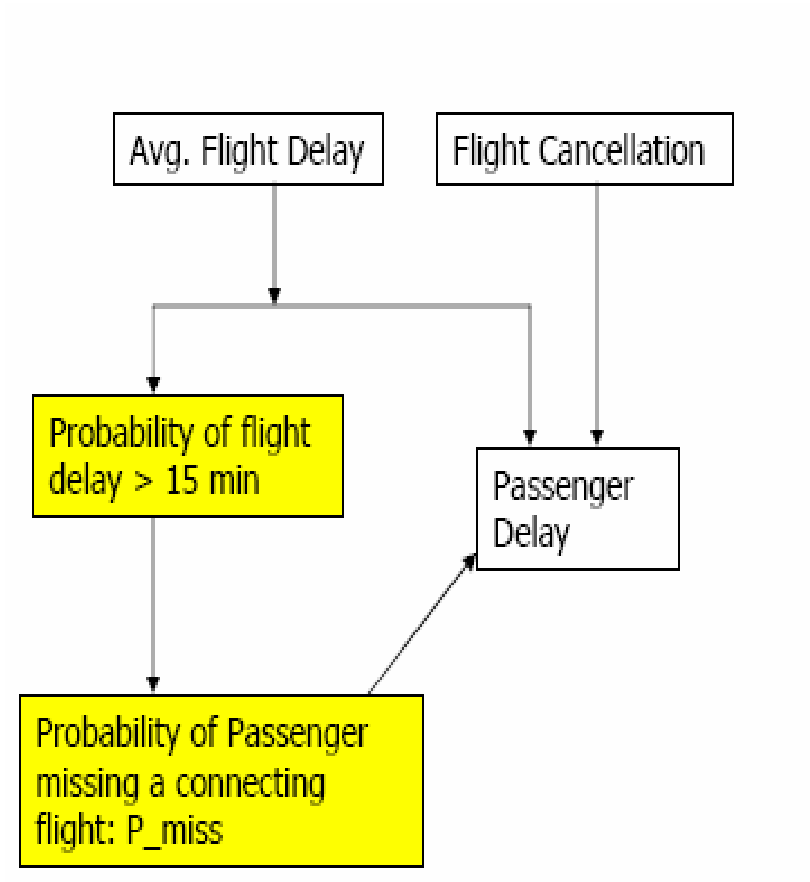


Figure 21 : Probability of passenger missing connecting flight

The following sections explain how the probability of flight being delayed and flight delay distribution can be obtained.

4.4.2 Probability of flight being delayed

As explained in section 3.5, we need to compute the probability that the flight is delayed – D_m. From the ASPM database, for each month from January 2000 to December 2004, we determine the following two metrics

- Average Flight delay in NAS
- % of flights delayed greater than 15 min

A flight is considered delayed only if its total delay minutes are greater than 15 min. The following plot shows % of flight delayed against average flight delay. Regression was performed with average flight delay as the independent variable.

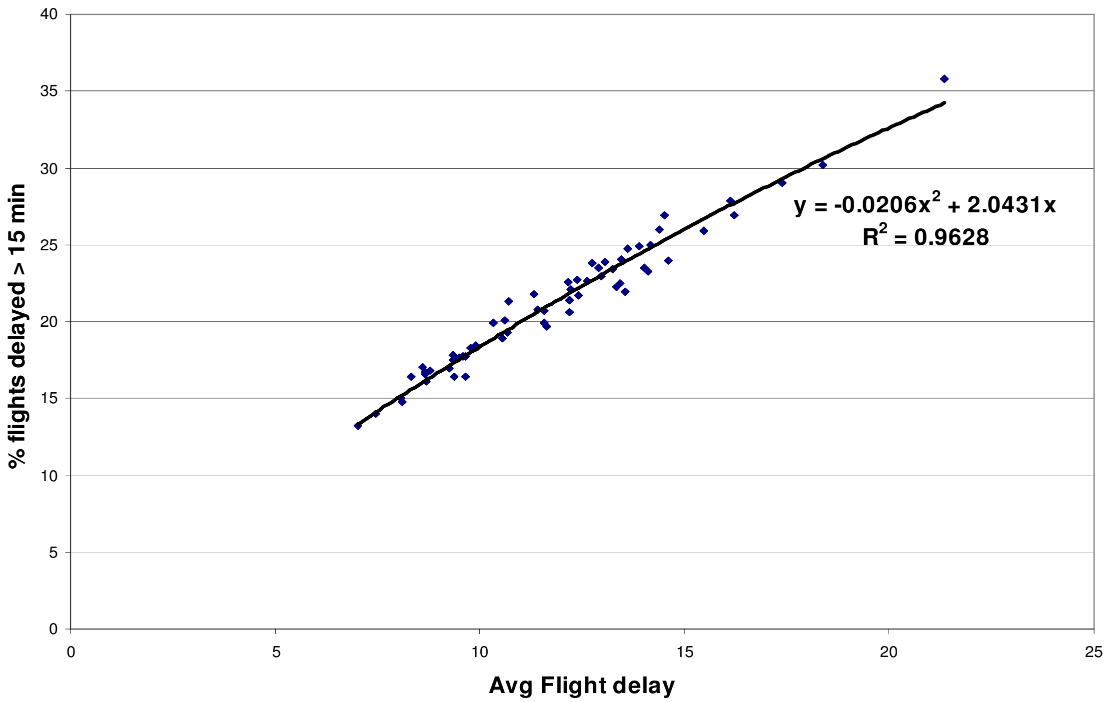


Figure 22 : Probability of flight being delayed

% of flights delayed = (-0.0206)* F_Delay*F_Delay + 2.0431*F_Delay

The model had an R^2 of 0.9628

4.4.3 Delay distribution of flights

The second step in determining the probability that a passenger misses connecting flight is the determination of flight delay distribution. The theoretical background was given in section 3.5. This section explains how flight delay distribution is estimated.. The following flowchart explains the procedure.

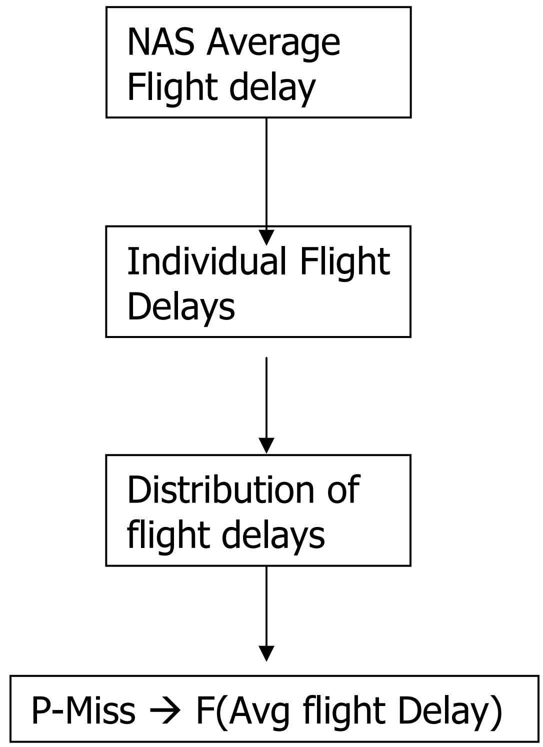


Figure 23 : Probability of passenger missing flight given average flight delay

From the ASPM database, we determine for each month, the average monthly delay. ASPM has an individual flights database. We use data from January 2000 to December 2004 for calibration. This database contains information about all the scheduled flights. They can be tracked through their tail numbers. It has information about their scheduled arrival time and actual arrival time. For each of the months, we create a histogram of the delay minutes. The percentage of flights that are delayed within discrete time intervals are found. (Time intervals of 15 min each). The following plots are examples of empirical flight delay distribution when average delay in NAS was 10 min, 15 min and 20 min respectively.

From ASPM, we know the average arrival delay in NAS for a given month. Now for each month, we determine the actual number of flights delayed in each of the time intervals 0-15,15-30,30-45 min etc. We determine the number of flights whose actual delay was in that interval. So, say for example, if the average flight delay is a month is 15 mintues, we find from individual flights database of ASPM , the actual number of flights that were delayed from 0-15 min, 15-30 min, etc. From this, we compute percentage of flights in each interval to obtain the empirical flight delay distribution. Given this data of flight distribution for each month given NAS delay, a delay distribution of flights for NAS was modeled which is conditioned on the average flight delay of NAS.

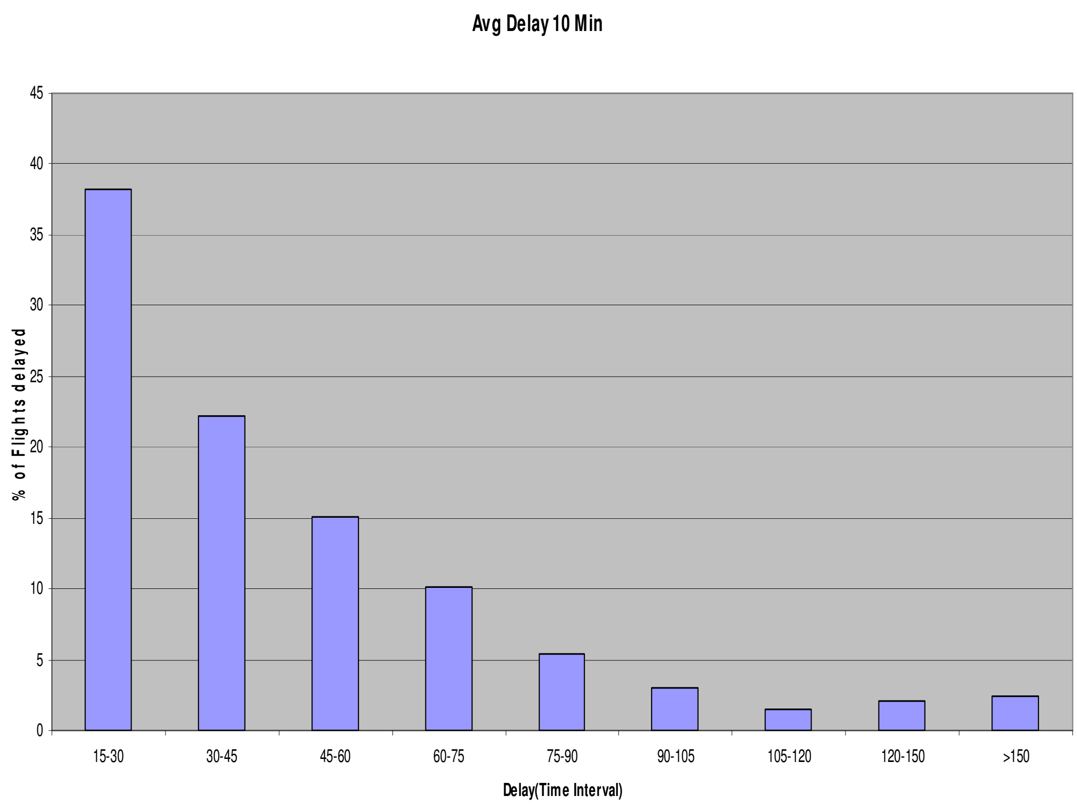


Figure 24 : Empirical Flight delay distribution with 10 min average flight delay

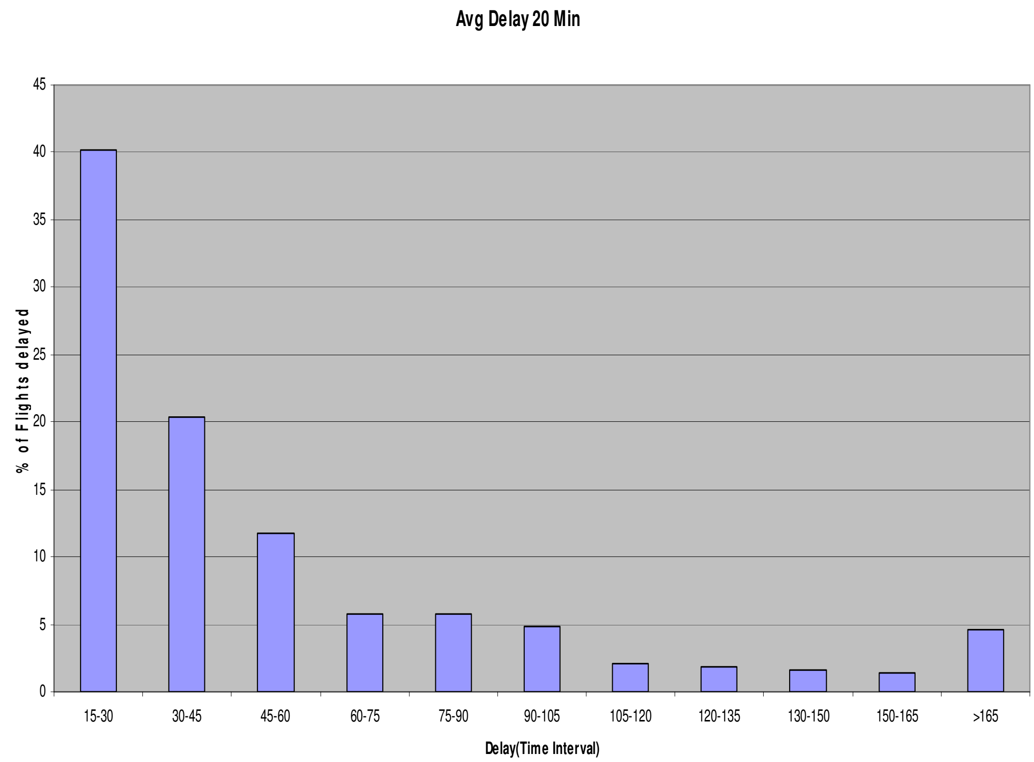


Figure 25 : Empirical Flight delay distribution with 15 min average flight delay

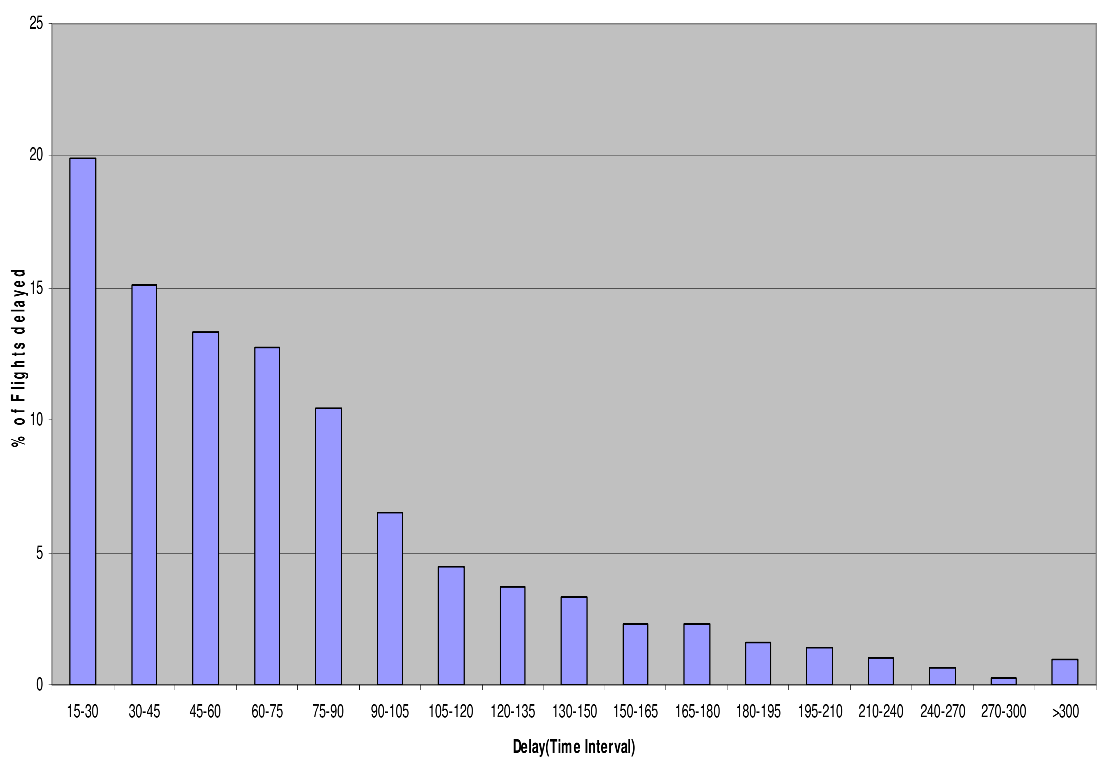


Figure 26 : Empirical Flight delay distribution with 20 min average flight delay

A Bi-Weibull distribution was fitted for the data obtained from 48 months.

The Bi-Weibull distribution is a combination of two weibull distributions and has 5 parameters:

x0 – point at which the parameters change.

(α1 , β1) and (α2 , β2) are parameters of the two weibull distributions

β2 is a function of the other 4 parameters.

One distribution for all months is determined by performing a regression the parameters of the Bi-weibull distribution for each of the months. The regression is carried out considering flight delays and flight cancellations as the independent variables.

The model results are as follows :

- X_0 = 11.1081 + 741.87F_Delay + .0104F_Cancel**2 R^2 = .93
- α_1 = 0.19 + 0.013F_Delay + 0.87*F_Cancel*F_Cancel R^2 = .87
- β_1 = 1.41 + .083F_Delay + 1.12F_Cancel**2 R^2 = .901
- α_2 = 0.487 + 0.0083F_Delay + .032F_Cancel R^2 = .82

The flight delay distribution is thus obtained as the bi-weibull distribution with the above parameters.

Goodness of fit for the bi-weibull distribution is shown below. Maximum likelihood Estimation(MLE) method was used to estimate the parameters and the low negative log likelihood showed that the model has been fitted well. In MLE, we seek the parameter values that are most likely to have produced the data. The regression coefficients were able to replicate the results of the bi-weibull distributions with minimal errors and hence it did not distort the distribution. In MLE, the objective is to maximize the likelihood ratio – hence lower the negative log likelihood, better is the fit. Hence a value closer to zero is considered good. For our model, negative log likelihood ratio of 7.5 or less is considered the threshold for acceptance. We can see that many of the months fell in this category, providing us with a very good fit.

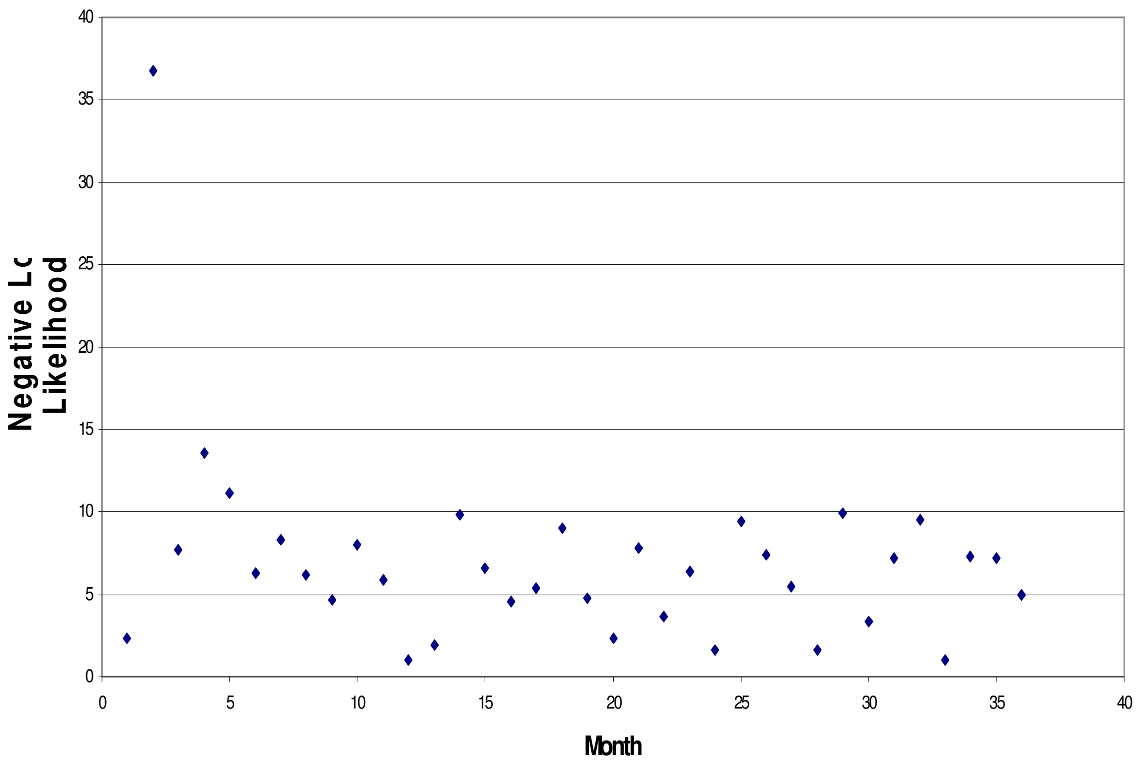


Figure 27 : Likelihood ratios for bi-weibull distribution

4.4.4 Passenger Delay Model

We have now given sources for all the parameters needed for the passenger delay model. The following plot shows the comparison of modeled passenger delay against actual average flight delay in the NAS from 2000 to 2004. It can be seen that as flight delay increases the passenger delay increases in a more than linear fashion. This supports our claim that as flight delays increase, more passengers are disrupted and the impact on passengers grows in a disproportionate manner.

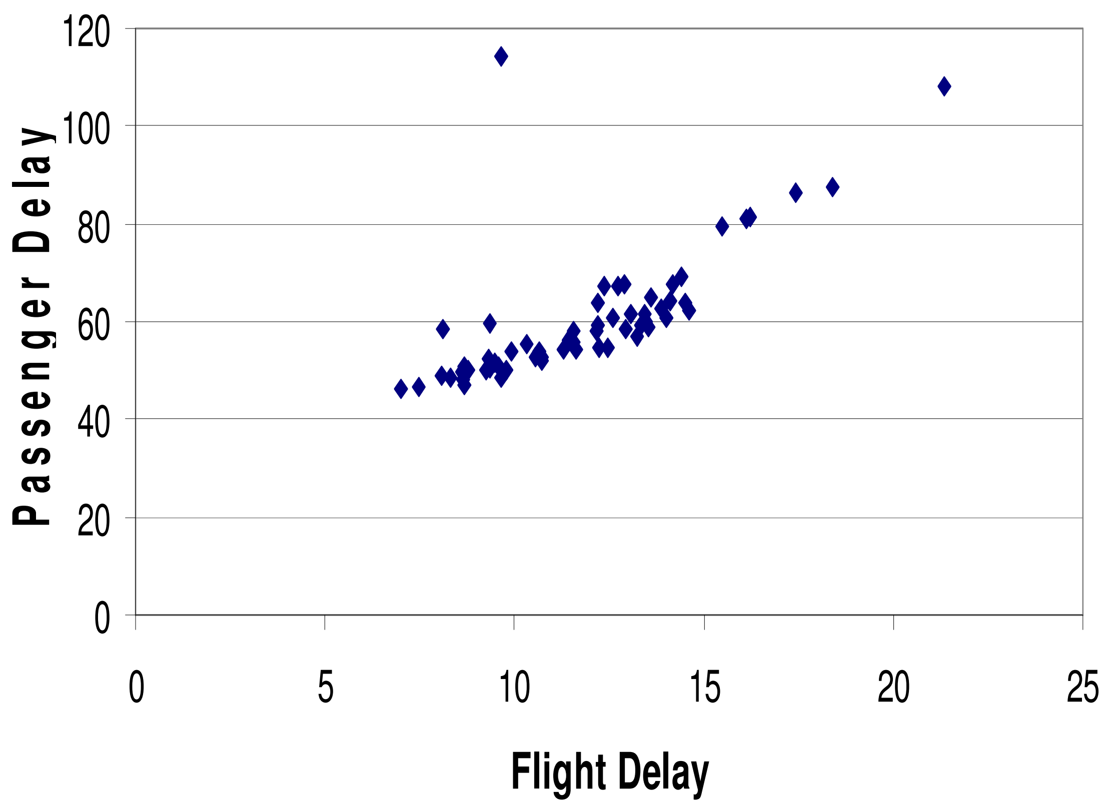


Figure 28 : Flight delays against passenger delays

4.5 Validation

In this section, we provide a validation of many of the models developed in this thesis.

4.5.1 Validation dataset

The models were calibrated using data available from ASPM from January 2000 to December 2004. The models are now validated using ASPM data from January 2005 to May 2006. Demand grew in 2005 and 2006 when compared to previous years. The validation dataset was also derived from ASPM database.

We computed all the input data required by the model from the raw data obtained from ASPM. From the demand and capacity in the 35 OEP airports, we computed NAS Rho 50, Rho 95 and Rho 99. We also had the convective weather index based on lightning strike data for the same period. We used the cancellation model to obtain the model's cancellation probability for the time period. Also, from ASPM we knew the actual cancellation rate that occurred. Similarly, we computed the model flight delay using all the input parameters. We obtained actual flight delays from ASPM database.

4.5.2 Validation of flight cancellations using aggregate monthly model

The following graph shows the comparison between actual cancellations and model cancellations. The model cancellation is computed using the model described in section 4.2.1. As can be seen, the model performs very closely to the actual cancellation. Though there are some errors between actual cancellations and model cancellations, we view the level of accuracy demonstrated to be quite satisfactory. Also, note that the model both over-predicts and under-predicts cancellation. Hence, the model does not exhibit any evident bias. The average least square error difference between the actual cancellation rate and the model cancellation rate is 2.7%

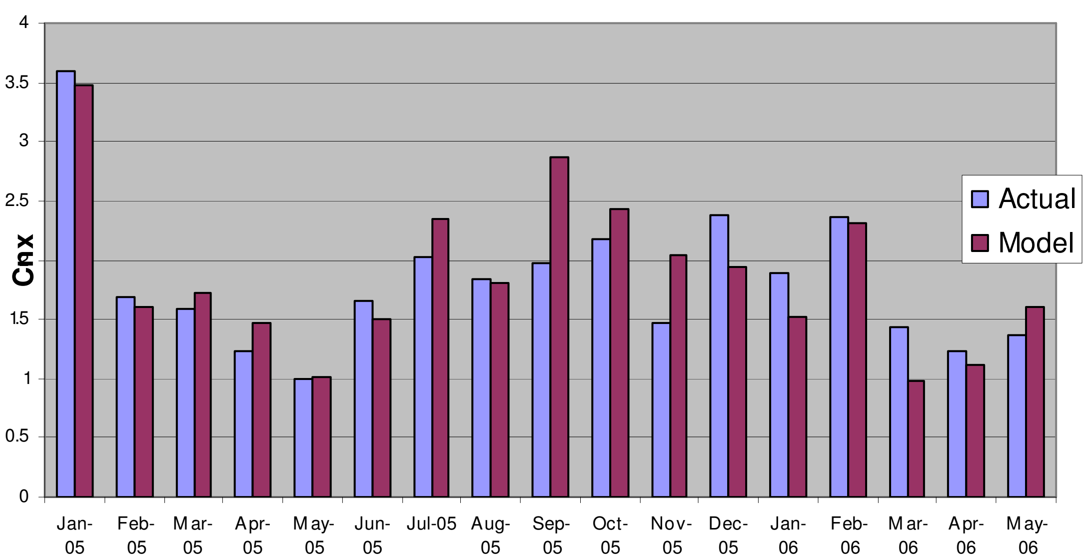


Figure 29 : Validation of flight cancellation considering NAS as a single system

4.5.3 Validation of flight delays using aggregate monthly model

The following graph shows the comparison between actual flight delays and model flight delays. The model flight delays are computed using the model described in section 4.2.2. Evidently, the model performs very closely to the actual flight delays. The average least square error difference between the actual flight delays and the model flight delays is 1.9 minutes.

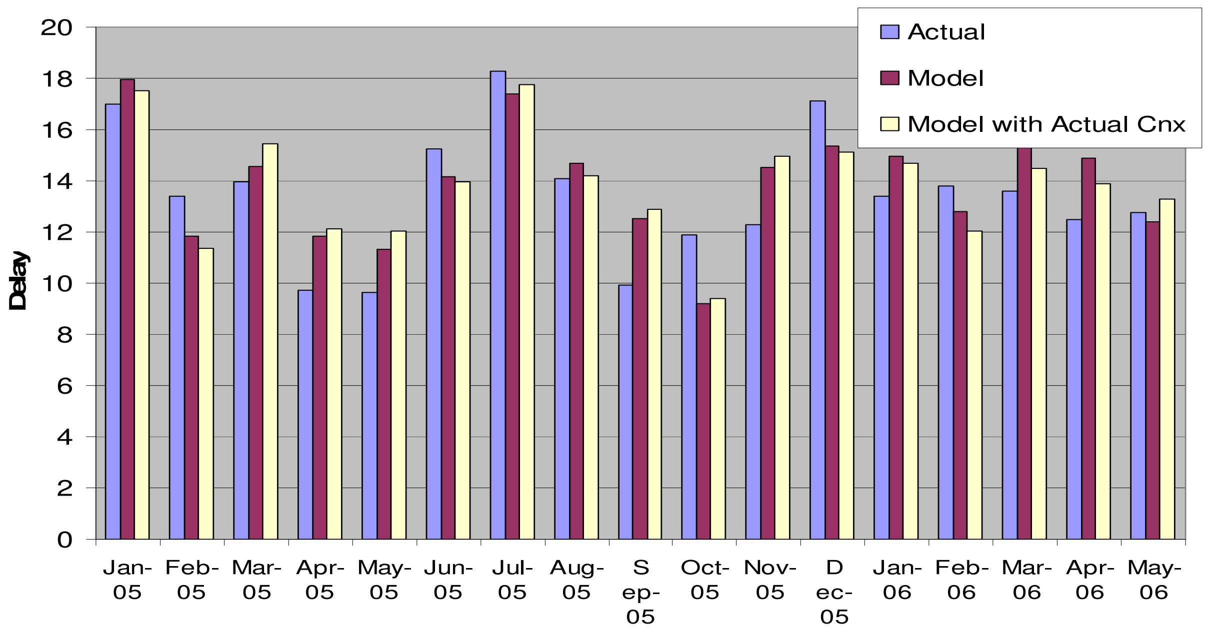


Figure 30 : Validation of flight delays considering NAS as a single system

The model both over-predicts and under-predicts flight delays. Hence, the model does not exhibit any evident bias. While validating flight delays, we use two approaches – one using actual cancellations and one using model cancellations. The graph shows clearly that increases in flight delays correlate with the decreases in cancellation.

4.5.4 Validation of flight cancellations using airport categories

Using actual data, the 35 OEP airports are categorized as before and for each of the categories, rho 50, rho 95 and rho 99 are computed. Having obtained all the necessary input data, the following graph shows the comparison between actual cancellations and model cancellations. The model cancellation is computed using the model described in section 4.3.1. As can be seen, the model performs very closely to the actual cancellation. The model both over-predicts and under-predicts cancellation. Hence, the model does not exhibit any evident bias. When compared with the model using NAS as a single system, the validation results from the clusters yield better results. The average least square error difference in the cancellation model in which NAS is considered as a whole system is 2.7% while in the cluster model, the average least square difference is only 1.65%. This can be explained by the fact that the effect of congested airports contributing more to the cancellation is better captured in the cluster model while in the NAS model, all airports are considered the same.

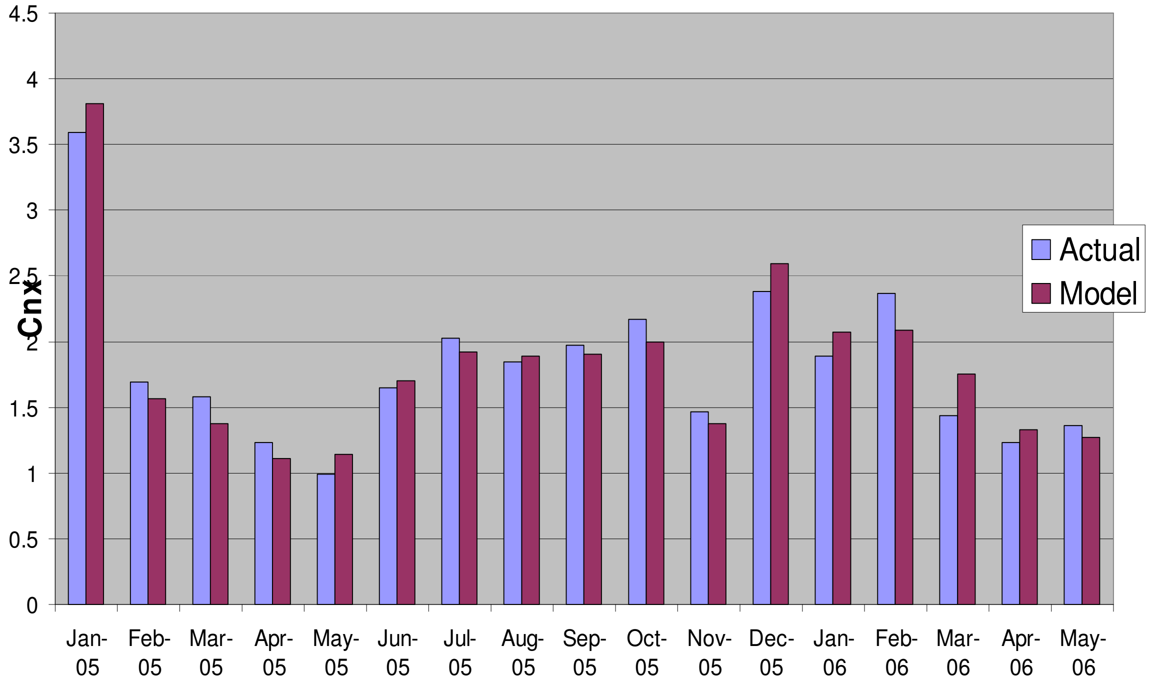


Figure 31 : Validation of flight cancellations considering airport categories

4.5.5 Validation of flight delays using airport categories

The following graph shows the comparison between actual flight delays and model flight delays. The model delay is computed using the model described in section 4.3.2.Evidently, the model performs very closely to the actual flight delays. The model both over-predicts and under-predicts flight delays. Hence, the model does not exhibit any evident bias. While validating flight delays, we use two approaches – one using actual cancellations and one using model cancellations. As in the case of cancellation validation, the delay validation is closer to the actual one in the cluster model than the delay model considering NAS as a single system. Delays are better captured and represented in the airport clusters.

The average least square error difference in the delay model in which NAS is considered as a whole system is 1.9 minutes while in the cluster model, the average least square difference is only 0.93 minutes. Severely congested airports contribute more to NAS delays than the other airports

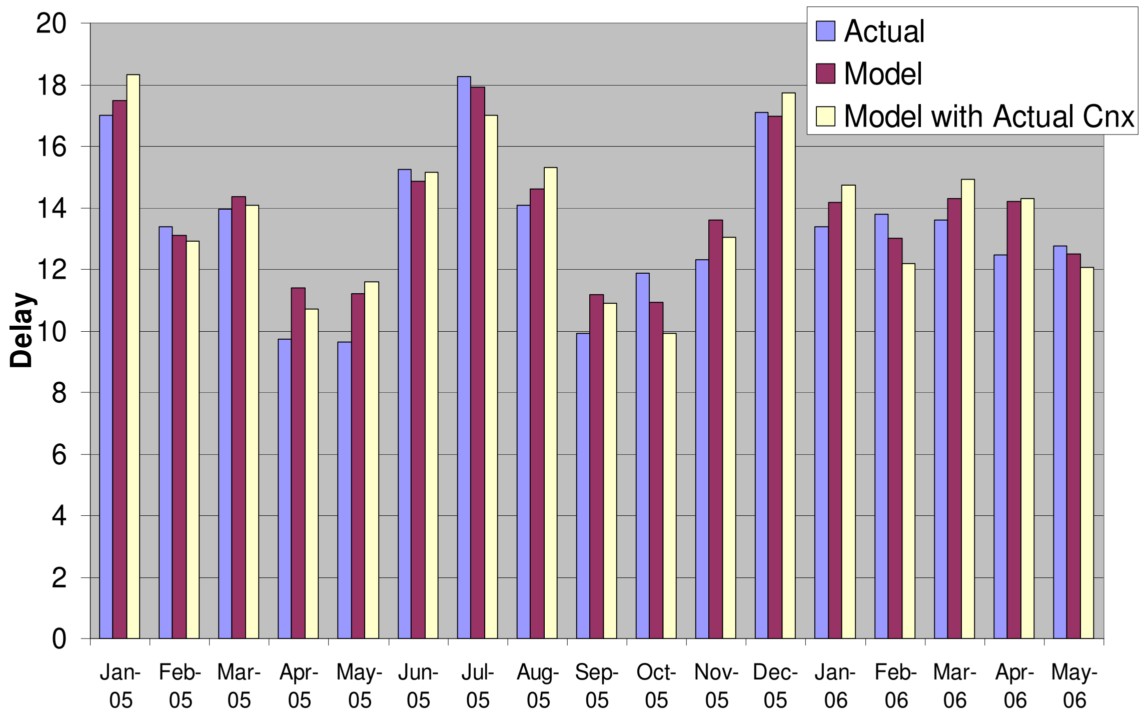


Figure 32 : Validation of flight delays considering airport categories

Chapter 5: CONCLUSIONS

In this thesis, three key monthly performance metrics for the national airspace system are developed.

- Average flight delay
- Flight cancellation rate
- Average passenger delay

Two different approaches were investigated for the aggregate modeling of delays and cancellations – one considering the whole NAS as a single system and the other using airport categories. The validation results showed that the models behave within acceptable limits and can be readily used in strategic decision support tools for high level performance metrics.

The passenger delay model takes into account several major factors that impact passenger delay. A limitation of this analysis is that we have not been able to validate the results because of the unavailability of passenger delay data. The model suggests that there will be large penalty for passengers in terms of delay-minutes whenever a flight is cancelled. That provides an explanation for why passenger experience varies from year to year as the overall cancellation probabilities change.

The most important contribution of this thesis is not the models developed, but rather, is the methodology developed. The models can be adjusted in response to changing application requirements. Our models include the main NAS factors and hence the ideas and techniques suggested should warrant consideration whenever high-level aggregate metrics for the system are required to evaluate performance. Many of the approximations used in the model were developed specifically keeping typical airspace traffic in mind.

5.1 Recommendations for Future Work

We envision the model will ultimately be available to traffic flow managers as well as carrier analysts for high level strategic decision support system. While the current model sufficiently captures system complexity of traffic, we believe a more accurate and robust approach to the problem could be developed if more factors were analyzed and used as explanatory variables in the model.

The two different approaches for flight delays and cancellation models that we developed in this thesis produced significant results. It is hoped that these models can be used in the future to estimate performance characteristics of demand growth scenarios. Thus, next research steps should include providing the flexibility necessary to respond to different scenario assumptions.

Appendix A: Regression Results for probability of flight cancellation model

Source	SS	MS		Number of obs = 420		
Model	5.76E+12	8.23E+11		Prob > F = 0.0000		
Residual	1.72E+12	5.26E+09		R-squared = 0.7081		
Dtot	Coef.	Std. Err	t	P>|t|	[95% Conf. Interval]	
a11	0.028333	72.27313	6.6	0	334.8867	619.2479
a12	0.0795526	0.033255	-2.81	0.005	-0.15887	-0.02802
a13	0.0794262	2.3984 4.	35 0.	000 5.	71299	15.14958
b11	0.0058226	27.21629	11.86	0	269.3207	376.4042
b12	0.0551185	12001.16	3.94	0	23664.47	70883.45
b13	0.0604216	0.031408	8.96	0	0.219691	0.343267
A21	0.0624469	0.029444	2.95	0.003	0.028928	0.144775
A22	0.0671915	39319.02	-5.61	0	-297952	-143250
A23	0.0095602	858.1677	3.841083	0.006828	69.43523	84.34123
B21	0.0132787	566.5377	7.068578	0.00271	47.99222	1.789983
B22	0.0146435	479.5134	5.929441	0.004249	88.28528	49.18204
B23	0.0658055	614.7718	2.589798	0.001293	91.35246	94.69672
A31	0.0283174	132.7262	8.269004	0.005763	4.197804	8.260735
A32	0.0209817	323.1366	9.11684	0.008616	22.07716	15.85133
A33	0.0644841	213.845	3.328312	0.000324	51.53345	25.90281
B31	0.0654879	108.7326	3.926726	0.009927	25.01773	38.41476
B32	0.0571152	165.5553	5.546565	0.005754	40.99603	25.48848
B33	0.0986086	711.3189	1.503322	0.008197	26.32615	81.00781
A41	0.0487056	514.0411	7.099995	0.006317	78.957	50.31184
A42	0.0911947	103.7697	8.860716	0.00217	94.88497	73.21385
A43	0.0558516	878.0298	9.77671	0.006067	60.76984	30.73305
B41	0.0130386	434.827	8.806123	0.00314	44.13077	21.17963
B42	0.0196012	866.235	8.274917	0.007361	61.68091	61.90078
B43	0.0044486	36.68946	1.703835	0.001911	40.09925	40.21134
A51	0.0481466	384.6953	4.502357	0.003867	82.82656	18.93526
A52	0.0592508	16.3201	9.577788	0.007716	87.55572	33.46164
A53	0.0536335	158.5535	4.56274	0.005837	38.89836	71.04318
B51	0.0497406	285.3747	8.861933	0.0005	85.94702	65.40754
B52	0.0744416	557.9226	0.526496	0.009915	92.8038	1.996732
B53	0.0736344	835.0588	7.759757	0.001904	51.85345	92.85831
A61	0.0252837	858.0042	5.348424	0.007772	79.17088	3.836374
A62	0.0123801	431.9125	2.913134	0.002981	42.75031	30.06307
A63	0.0484111	106.8682	5.753742	0.009073	60.35721	44.62224
B61	0.0295848	747.3557	3.025311	0.007862	40.13058	71.15808
B62	0.0712704	62.29113	4.784929	0.002791	3.037783	55.80097
B63	0.0888003	24.71136	2.833942	0.007737	72.19605	12.98287
A71	0.0263699	568.7611	5.011988	0.005269	11.28533	57.578
A72	0.098027	404.1063	8.952685	0.002601	21.55692	76.863
A73	0.0658882	380.171	4.261206	0.007134	28.67905	66.65966
B71	0.0787937	377.5801	2.921173	0.006201	86.41214	5.779316
B72	0.0596786	563.1387	8.632057	0.005858	68.38847	38.28234
B73	0.0585528	467.5914	5.117833	0.008984	89.39038	74.43727

Appendix B: Regression Results for probability of flight delay model

Source	SS	MS		Number of obs = 420		
Model	5.73E+12	8.23E+11		Prob > F = 0.0000		
Residual	2.13E+12	5.26E+09		R-squared = 0.7212		
Dtot	Coef.	Std. Err	t	P>|t|	[95% Conf. Interval]	
a11	0.5225486	72.27313	6.6	0	334.8867	619.2479
a12	0.6996107	0.033255	-2.81	0.005	-0.15887	-0.02802
a13	0.9617166	2.3984 4.	35 0.	000 5.	71299	15.14958
b11	0.5881864	27.21629	11.86	0	269.3207	376.4042
b12	0.6352046	12001.16	3.94	0	23664.47	70883.45
b13	0.0928357	0.031408	8.96	0	0.219691	0.343267
A21	0.629398	0.029444	2.95	0.003	0.028928	0.144775
A22	0.9769543	39319.02	-5.61	0	-297952	-143250
A23	0.9154648	582.9623	9.787392	0.009514	15.47897	13.05097
B21	0.1039108	75.99329	1.385639	0.006835	83.08252	70.83523
B22	0.9679555	649.394	1.786555	0.006238	60.17275	51.75938
B23	0.1672173	761.6755	1.848803	0.000351	71.43795	50.11962
A31	0.2491024	676.0076	1.736607	0.000344	81.61498	71.33649
A32	0.2921272	516.3533	4.131502	0.000114	80.68177	78.12585
A33	0.7507797	22.01669	1.01349	0.009971	85.46861	44.75873
B31	0.5417039	332.6256	2.672057	0.001269	43.84186	46.05379
B32	0.6835583	968.1588	0.254482	0.00158	25.21338	48.27661
B33	0.5561152	922.1775	8.723871	0.000416	46.99396	69.21593
A41	0.8832974	500.6322	3.049236	0.004437	10.09477	31.366
A42	0.4420076	229.9837	5.991177	0.000724	67.35826	11.06842
A43	0.7781264	962.0675	2.771278	0.007618	37.09889	94.83681
B41	0.1715647	705.448	1.922725	0.009195	51.59775	47.50689
B42	0.6144884	667.3276	5.544187	0.006384	90.21644	73.63098
B43	0.2681502	453.0594	6.201882	0.002323	38.6521	69.07982
A51	0.9535851	392.3584	4.748856	0.008859	83.03614	31.83565
A52	0.5088752	287.5331	7.349197	0.009334	35.06619	33.08298
A53	0.8190684	642.2384	3.54561	0.001913	89.30996	54.47863
B51	0.8943044	511.8747	5.924426	0.007008	75.35383	46.06529
B52	0.4354418	155.5949	9.033118	0.001915	40.32467	8.903997
B53	0.1361126	596.3502	9.335469	0.005449	70.15769	53.82654
A61	0.830572	953.6881	2.542016	0.004209	4.190075	9.624832
A62	0.8675991	584.7611	7.361364	0.007689	82.06948	3.86533
A63	0.041131	910.0771	7.168479	0.005771	95.65605	67.78822
B61	0.7207658	42.706	7.032396	0.006315	11.58556	37.18383
B62	0.9677927	163.1957	2.952706	0.003264	96.06433	83.65818
B63	0.0020336	407.2764	9.577403	0.00456	54.13956	83.41017
A71	0.095967	617.033	2.368694	0.008888	61.55224	67.82623
A72	0.2126361	666.3502	1.030312	0.000801	1.609959	84.29244
A73	0.2783354	616.1546	9.028457	0.008148	85.88095	94.24163
B71	0.9003365	385.7724	6.435057	5.96E-05	98.46564	74.54139
B72	0.5028355	437.5448	9.517077	0.006458	70.93237	59.88279
B73	0.5131882	535.2781	3.393867	0.001266	18.88705	63.99985

Appendix C: Computing Passsenger Delay for a month

For the month of January 2000,

Average monthly delay = 13.62 minutes

Cancellation probability = 3.08%

F_Direct = 0.66

P_Del_Disrupt = 420 min

Lay – Connect = 30 min

% of flights delayed > 15 min = 24% (from section 4.4.2)

To compute P_Miss , from section 4.4.3

X_0 = 36.62

alpha1 = 0.57

alpha2 = 0.35

beta1 = 49.65

beta2 = 22.95

Hence P_Miss is the probability that passenger missing connecting flight = 0.1134

Using scenario tree formula,

We compute P_Delay = 45.023 minutes

Bibliography

[1] Callaham, M.B., J. S. DeArmon, A. M. Copper and J. H. Goodfriend. Assessing NAS performance: Normalizing for the effects of weather. *4th USA/Europe Air Traffic Management R&D Symposium*, 2001

[2] Wieland, F. Estimating the Capacity of the National Airspace System. *24th Digital Avionics Systems Conference*, November 2005.

[3] Post, J and D. Murphy. Regression Model of National Airspace System Delay . *ATIO Conference*, September 2006

[4] Post, J, J. Bonn, M. Bennett and D. Knorr, The Use of Flight Track and Convective Weather Densities for National Airspace System Efficiency Analysis. *21st IEEE/AIAA Digital Avionics Systems Conference*, October 2002.

[5] Bratu, S and C. Barnhart. An analysis of passenger delays using flight operations and passenger booking data. *Air Traffic Quarterly*, volume 13(1) 1-27, 2005.

[6] Wang, D and L. Sherry. Trend Analysis of Airline Passenger Trip Delays. *Transportation Research Board*, 2007.

[7] Mukherjee, A., Lovell, D., Ball, M., Odoni A. and Zerbib, G., "Modeling Delays and Cancellation Probabilities to Support Strategic Simulations", in *Proceedings of 6th USA/Europe Air Traffic Management R&D Seminar*, 2005.

[8] Chatterji, G.B and B. Sridhar. National Airspace System Delay Estimation Using Weather Weighted Traffic Counts. *AIAA Guidance, Navigation and Control Conference*, *San Francisco, CA*, 2004.

[9] Sridhar, B and S M Swei. Relationship between Weather, Traffic and Delay Based on Empirical Methods. *ATIO Conference*, September 2006

[10] Klein, A, R. Jehlen, D. Liang, Weather Index with queuing component for National Airspace System performance assessment, in *Proceedings of 7th USA/Europe Air Traffic Management R&D Seminar*, 2007.

[11] Bratu, S. Airline Passenger On-Time Schedule Reliability: Analysis, Algorithms and Optimization Decision Models. *Ph.D Thesis*, *Massachusetts Institute of Technology, Cambridge, MA*, 2003

[12] Wang, D , L.Sherry and G. Donohue. Passenger Trip Time Metric for Air Transportation. *The 2nd International Conference on Research in Air Transportation*, *Belgrade, Serbia and Montenegro*, June 2006.

[13] Airline On-Time Performance Data. *Bureau of Transportation and Statistics*. http://www.transtats.bts.gov/Tables.asp?DB_ID=120&DB_Name=Airline%20OnTime%20Performance%20Data&DB_Short_Name=On-Time

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

[15] Federal Aviation Administration, *Aviation System Performance Metrics (ASPM)* [online database], URL: http://www.apo.data.faa.gov/aspm/entryASPM.asp

[16] Federal Aviation Administration, *Knowledge Sharing Network* URL : https://ksn.faa.gov/km/atop/nssg/default.aspx