Airport Capacity and Regional Weather Modeling

by

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Abstract

Airport weather variables, including cloud ceiling, horizontal visibility, and wind, significantly influence the capacity of an airport. In this thesis, the sawtooth wave model, a statistical weather model with the capability to generate synthetic weather observations useful in air traffic flow management simulations, is presented. The sawtooth wave model uses historical weather data as input and produces synthetic weather observations that preserve the spatial correlation values of weather observations among sites, temporal correlation values of weather variables at each site, and cross-correlation values between weather variables.

Four capacity models that are driven by weather observations, either historical or those generated by the sawtooth wave model, are also presented. None of the models are ideal in that all of them have some weakness but each of the models also have strengths that should be captured in an ideal model. In spite of the limitations of the individual models, the capacity information gathered from simulation runs using these models allows us to draw conclusions about airport capacities from airport characteristics.

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The Charles Stark Draper Laboratory, Inc.
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1. Introduction

1.1. Background

The United States has the largest and most concentrated airspace system in the world. The National Airspace System (NAS) and the demand for its resources is continuing to grow. Flights in the United States are regularly experiencing unacceptable levels of delay. Some predict that by the year 2000, there will be 800 million passengers a year [1]. This is nearly twice the number of passengers in 1990. Thus, delays are not going to disappear but could get worse if the situation is not addressed.

Due to high density of traffic in terminal areas, airports are arguably the most important element in flow management strategies. For example, when an airport such as Chicago’s O’Hare or New York’s LaGuardia becomes saturated, the delays caused by this saturation result in a propagation of delay throughout the system. When these airports, called pacing airports, experience congestion and capacity problems, the effects are generally felt by the entire system. Similarly, if all of the pacing airports are operating smoothly, the entire system does well. By focusing on ways to improve efficiency, increase capacity and reduce delay at these pacing airports, we can greatly improve the overall efficiency of the entire system.

Empirical evidence shows that weather is the dominant factor in influencing an airport’s capacity. The FAA maintains that 65% of all delays in the air traffic system are weather related [2]. The parameters that are used to describe airport weather are cloud ceiling, horizontal visibility and wind. Low ceiling and/or visibility observations require increased spacing intervals between operations, both arrivals and departures, and thus decrease the capacity of an airport. Maximum crosswind constraints eliminate the choice of certain runways and subsequently eliminate some runway configurations. It is therefore essential to consider airport weather in any analysis of the air traffic system.

There is not much in the literature on weather models suitable for use in the analysis of the NAS. Often when air traffic simulations are run and weather data is needed as input,
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historical weather data has been used. Instead, the focus of work has been development of new
airport capacity models and upgrading older models.

In the past, arrival capacity was the focus of airside capacity models. It was assumed
that departures could be inserted in between arrivals to meet departure demand. Arrival capacity
was considered the bottleneck that caused congestion and delays. With deregulation and the
incorporation of hub and spoke systems, many airlines have large arrival and departure banks at
the pacing airports. This means that there are times when a pacing airport may undergo a wave
of arrivals followed by departures. Therefore, it has become important to consider departure
capacity and the tradeoff between arrivals and departures in analyzing capacity. This type of
capacity analysis must be considered in developing air traffic flow management strategies.

1.2. Thesis Objective and Content

The research and models presented in this thesis provide a basis for future air traffic flow
analysis. This thesis summarizes two components which will be included in a simulation
environment for air traffic flow analysis — weather and capacity.

Chapter 2 presents the first area of research — airport weather. The first part of the
chapter describes the weather elements that affect an airport’s operations and can limit its
capacity. In the second part we provide an overview of different statistical functions is given.
These functions are needed to implement the sawtooth wave model, a statistical weather model
developed by the United States Air Force [12], described in the third part of the chapter. In the
model description we summarize the basic elements of the model as well as extensions made to
the model to incorporate new weather elements. Next, data observations synthetically generated
are compared with historical data to validate the model. Finally, a limitation of the weather
model as well as possible solutions to this limitation are discussed.

Chapter 3 presents four different capacity models. The capacity models use weather
observations as input in a simulation environment and provide insight about capacity levels at an
airport. The four models examined are: Empirical Data Capacity Frontiers developed by E.
Gilbo at the Volpe Center [15], Engineered Performance Standards compiled by the Federal
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Aviation Administration (FAA) [18], the *FAA Airfield Capacity Model* created by W. Swedish at the MITRE Corporation [17], and the *LMI Airfield Capacity Model* developed at the Logistics Management Institute [20].

Chapter 4 describes the process used to compare and evaluate the different capacity models. Different metrics used to compare the models are presented. Information about the capacity of an airport may be inferred by the airport’s characteristic based on the results of simulation runs used to evaluate the different capacity models. These results and inferences are presented also presented in the chapter. Strengths and weaknesses of each of the different models are discussed. Finally, a design for a future capacity model is described.

In Chapter 5, conclusions from the results of analyses using the combined weather/capacity simulation capability are presented and topics for future related research are discussed.
Chapter 1: Introduction
2. Weather Modeling

One goal of this project is to implement an accurate weather model to produce synthetic weather observations at pacing airports. An accurate weather model is one in which synthetic data produced by the model are statistically indistinguishable from historical data for the same region and time interval.

We extended the weather model in Hocker[3] to use the tetrachoric correlation method (discussed later in subsection 2.2.1 Pearson Product Moment vs. Tetrachoric) and to generate synthetic wind observations. This model was implemented in C and is portable.

In section 1, we describe the elements that compose airport weather. In section 2, we present two different techniques for measuring correlation and when to use each one. Section 3 provides a description of the sawtooth wave model. In section 4, we analyze the results of using the sawtooth wave model. Section 5 describes a limitation of the sawtooth wave model and how to circumvent this limitation. Section 6 concludes the chapter.

2.1. Airport Weather

The term airport weather will refer to those components of weather that most affect airport capacity. These components are cloud ceiling, visibility, wind speed, wind direction and precipitation. All of the historical weather data used was procured from the National Oceanic and Atmospheric Administration (NOAA).

2.1.1. Cloud Ceiling and Visibility

Cloud ceiling, or simply ceiling, is defined as the base height of the lowest cloud that is more than 1/2 opaque in an airport area. Ceiling measurements are taken to the nearest 100 feet up to 5000 feet, to the nearest 500 feet from 5000 to 10000 feet, and to the nearest 1000 feet for observations above 10000 feet [4].

Visibility refers to the prevailing horizontal visibility, usually measured at an elevation of 6 feet above the ground. These measurements are taken to the nearest sixteenth of a mile up to 3/8 mile, to the nearest eighth of a mile up to 1 3/4 mile, to the nearest fourth of a mile up to 3
Chapter 2: Weather Modeling

miles, and to the nearest mile after three miles [4]. There is also an unlimited classification, used when the visibility is greater than 10 miles.

The values for ceiling and visibility determine the flight rules classification of an airport. Low ceiling and/or low visibility result in an Instrument Flight Rules or IFR classification. During IFR operation, aircraft may conduct landings only on runways with special landing equipment. Both the aircraft and its crew must also be IFR rated. In good weather conditions, where there is a high ceiling and high visibility, the airport will be given a classification of Visual Flight Rules or VFR. In general, the capacity of an airport under IFR conditions is much less than the capacity of the airport under VFR conditions because landing and departure intervals tend to be greater under IFR conditions. These basic classifications also have sub-classifications that further differentiate weather conditions. IFR conditions are broken up into IFR1 and IFR2. IFR2 (also be referred to as Low IFR or LIFR) refers to severe weather conditions where visibility and/or ceiling is extremely low. Some airports shut down completely when this occurs and no aircraft are allowed to land or depart. VFR conditions are broken into VFR1 and VFR2 (sometimes called Marginal VFR or MVFR). The division between VFR1 and VFR2 is different for each airport and is determined by obstructions in the vicinity of the airport. Marginal VFR conditions require a ceiling of at least 1000 feet and a visibility of three nautical miles. VFR1 conditions occur when the cloud ceiling is at least 1000 feet higher than the height of the tallest structure in the vicinity of the airport and the visibility is at least 5 nautical miles [21]. The figure below illustrates these classifications for an example airport.
Chapter 2: Weather Modeling

2.1.2. Wind Speed and Direction

Wind is another important weather element in determining the capacity of an airport. Wind conditions, both speed and direction, can restrict the availability of runways. Given a particular runway, the prevailing wind vector can be decomposed into two components, a headwind component and a crosswind component. The headwind component blows against the direction of the runway. For example, if an aircraft will be landing on a runway from east to west, the headwind would be the component that blows from west to east. If the wind were blowing in the direction of the runway, it would have a negative value for the headwind component and would simply be referred to as a tailwind (with positive value). The crosswind, on the other hand, is the portion of the wind that blows across the runway; this would be the north-south or south-north component in the previous example. Figure 2.2 illustrates the different wind vector components.
Each airport has a maximum crosswind, regardless of direction, allowed for an active runway. Usually this value is somewhere between 15 and 20 knots and sometimes varies based on flight rule conditions. For example, a runway may have a 20 knot maximum allowable crosswind during VFR conditions but only a 15 knot maximum allowable crosswind during IFR conditions. When a runway is not allowed to be used, it is inactive. All airport configurations that include inactive runways are considered inactive, limiting the airport’s capacity.

When considering headwinds, direction is important. With a headwind, the effective stopping distance of a plane is shorter than when there is no headwind. Planes can then move off the runways more quickly, freeing the runway for other operations and reducing the time spent on an active runway. Similarly, throughput is increased when planes take off into a headwind because shorter runway distances are needed for lift. Therefore, operating with a headwind improves both the arrival and departure capacities and increases safety. In fact, at many airports no tailwind is allowed; at some of the busier airports a five knot tailwind is allowed.

Depending on the composition of airport demand, tower controllers can designate runways with headwinds as arrival or departure runways to increase overall throughput of the airport. For example, if the demand composition was 80% arrivals and 20% departures, then an air traffic controller might choose to use a runway with a strong headwind as the arrival runway.
2.1.3. Precipitation

Precipitation impacts the capacity of an airport in many ways making it difficult to model. Increased runway length is needed when the runways are wet. When de-icing of a plane is required, departure rates decrease. The current weather model does not include precipitation but may be included in the future after several issues are addressed. For example, it is unclear whether the amount of precipitation or the mere presence of precipitation is the most important factor in airport capacity analysis. Similarly, we must determine what the effects of different types of precipitation (e.g. rain, snow, ice) have on capacity. One final issue of concern is the duration of the precipitation. Longer landing distances are needed for pavement which has just become wet than on pavement which has been wet for some time. Thus, capacity may be less at the beginning of a rainstorm than in the middle of one.

It is clear that precipitation limits an airport’s capacity but until we identify which components of precipitation affect capacity, incorporation of precipitation into the model is not practical.

2.2. Correlation

Correlation is a measure of the relatedness or association among variables. Statistically, correlation can be quantified by the theoretical coefficient of correlation $\rho_{xy}$ between two random variables $X$ and $Y$ [5]. This corresponds to the ellipticity parameter in the bivariate normal distribution. In other words, if two random variables are joint, normally distributed, then $\rho_{xy}$ measures the strength of the linear relationship between the two random variables. Given $X$ and $Y$ are two random variables with respective means of $\mu_X$ and $\mu_Y$ and standard deviations of $\sigma_X$ and $\sigma_Y$, then

$$
\rho_{xy} = \frac{\sigma_{xy}}{\sigma_X \cdot \sigma_Y}
$$

(2.1)

where the covariance

$$
\sigma_{xy} = \text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]
$$

(2.2)
Chapter 2: Weather Modeling

Equations (1) and (2) can reflect both positive and negative correlation. If related values of \(X\) and \(Y\) vary from their respective means in the same direction, the resulting covariance will be positive. Conversely, if \(X\) and \(Y\) vary in opposite directions from their means, the covariance will be negative resulting in negative correlation.

2.2.1. Pearson Product Moment vs. Tetrachoric

In generating synthetic weather using the weather model described in this paper, accurate estimates of the ellipticity parameters are needed. These correlation coefficients are estimated using one of two methods: Pearson Product Moment (PPM) or tetrachoric.

When estimating a correlation coefficient of joint, normally distributed random variables \(X\) and \(Y\), one can use the PPM formula

\[
 r_{xy} = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2}} 
\]  

(2.3)

where \(X_i\) and \(Y_i\) are sample observations, and \(\bar{X}\) and \(\bar{Y}\) are sample means. Both \(\rho\) and \(r\) can vary between -1.0 (perfect negative correlation), and 1.0 (perfect positive correlation). When the random variables \(X\) and \(Y\) are joint, normally distributed, \(r_{xy}\) is an unbiased estimator for \(\rho_{xy}\). In other words, the expected value of \(r_{xy}\) is equal to the value \(\rho_{xy}\).

The PPM formula, however, produces a biased estimator \(r_{xy}\) when the random variables are not joint, normally distributed. Cloud ceiling is a random variable which is not normally distributed since its lower limit is zero. Also, the precision of ceiling data decreases as ceiling measurements increase (i.e. a true ceiling of 10600 feet and 11400 feet would both be recorded as 11000 feet whereas a true ceiling of 600 feet and 1400 would be recorded as 600 feet and 1400 feet) and thus the data is subject to quantization error.

In this case, a more accurate estimator of \(\rho_{xy}\) is the tetrachoric correlation. The \textit{tetrachoric correlation} is defined as the correlation in a bivariate normal distribution that would be produced if the continuous normal variables observed were reduced to binary variables by dichotomizing observed values as either above or below a given threshold [6].
Chapter 2: Weather Modeling

To obtain the tetrachoric correlation, a threshold value is chosen for random variable \( X \) and a threshold value is chosen for random variable \( Y \). Usually median values are good choices for thresholds, but any value in the 20th to 80th percentile will produce relatively accurate results. Given the thresholds, one then counts the number of data points in the different quadrants defined by the thresholds as shown in Figure 2.3.

![Figure 2.3: Data Partitions](image)

**Figure 2.3: Data Partitions**

A is the number of data points whose \( X \)-value is below the threshold for \( X \) and whose \( Y \)-value is less than the threshold value for \( Y \); B is the number of data points whose \( X \)-value is above the threshold for \( X \) but whose \( Y \)-value is below the threshold value for \( Y \). Similarly, C is the number of data points whose \( X \)-value is below the threshold for \( X \) but whose \( Y \)-value is above the threshold for \( Y \). Finally, D is the number of data points whose \( X \)- and \( Y \)-values are above their respective thresholds. Given these four counts one can get an approximation of the tetrachoric correlation. A simple approximation is given by:

\[
\hat{\rho} = \sin \left[ \frac{\pi \sqrt{AD} - \sqrt{BC}}{2 \sqrt{AD} + \sqrt{BC}} \right]
\]  

(2.4)

This equation was derived from the first term of a Taylor series (Johnson and Katz [7] or Castellan [8]) and is accurate when both variables are dichotomized at the median. Because choosing the median as a threshold is not always easy or feasible, a more robust approximation able to use various threshold values is desired. Boehm [6] added additional terms to the above
approximation to yield a highly accurate estimated correlation for threshold values anywhere between the 20th and 80th percentile of the observed data. Boehm’s more accurate approximation was used to compute the correlation statistics for this study.

Table 2-1 shows which method to use to estimate correlation between airport weather variables.

Table 2-1: Correlation Calculation Methods

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Wind in each direction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ceiling</td>
</tr>
<tr>
<td>Ceiling</td>
<td>not normal</td>
</tr>
<tr>
<td>Visibility</td>
<td>not normal</td>
</tr>
<tr>
<td>X-vector</td>
<td>normal</td>
</tr>
<tr>
<td>Y-vector</td>
<td>normal</td>
</tr>
</tbody>
</table>

Because ceiling and visibility observations are not normally distributed, the tetrachoric method of estimating correlation is used when either of these variables is used. Only when correlating two normally distributed variables such as x-vectors with y-vectors should PPM be used.

2.2.2. Spatial Correlation

Spatial correlation between two sites is the correlation of the observations of a given weather variable as a function of the separation distance between the sites. The correlation among different geographic regions will vary according to the stability of the weather patterns and seasonal aspects. Figure 2.4 depicts a 30-year, average spatial correlation curve (using the tetrachoric correlation estimator) for cloud ceiling for sample sites in midwestern states for the month of July, compiled by the Air Force [9].
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Figure 2.4: Ceiling Spatial Correlation - Midwestern States

For sites which are within 500 miles, a positive correlation exists for ceiling observations. This correlation is weaker as the sites are further apart. Between 500 and 1000 mile separation distances there exists a negative, albeit weak, correlation. This may be attributed to fronts that move over a region and produce severe stormy conditions followed by favorably clear weather conditions and vice versa [22]. For sites over 1000 miles apart, there was some indication of positive correlation due to this same effect. However, because of the variability in weather according to geographic regions, correlation values for sites with separation distances over 1000 miles or even 500 miles should not be used.

Spatial correlation is an important component of an accurate weather model because it reflects the relatedness of weather conditions—and thus capacity problems—at neighboring airports. Accounting for simultaneous capacity problems at neighboring airports makes it easier to develop an air traffic flow management (ATFM) strategy that improves the overall efficiency of the air traffic system. Consider the congestion and capacity problems that occur along the northeast corridor specifically at the New York, Boston, and Washington airports. These airports often operate at high levels of demand close to their maximum throughput capacity. When weather conditions are poor and cause problems at one airport, operations at the other two airports can also be adversely affected due to flight interdependencies. Also, if the weather is the
reason for capacity decreases at one of these airports, it is not unlikely that airports at the other two sites are also influenced by the same weather pattern. Therefore, it is advantageous to evaluate ATFM strategies in a simulation environment which preserves correlation values.

2.2.3. Temporal Correlation

Temporal correlation, also referred to as serial correlation, refers to the auto-correlation of weather observations in the time domain. One way to model the transient and dynamic aspects of weather is to capture the relationship between time-series values of a variable.

Temporal auto-correlation for a weather variable can be measured by calculating the lag $s$ auto-correlation of sample observations, where $s$ represents the time interval between observations [Hocker]. The Pearson Product Moment formula in equation (2.3) or the tetrachoric formulation in equation (2.4) can be used to calculate auto-correlation. Instead of pairing X- and Y-values at the same time such as ceiling observation in Boston at time $t$ vs. ceiling observation in New York at time $t$, the X- and Y-values will be at the same site but at different times. For example, if the temporal correlation for visibility in Boston with a lag of $s$ is desired, Y-values would be visibility observations in Boston at time $t$ and X-values would be visibility observations in Boston at time $t-s$. If there are $N$ discrete observations then Y-values would have a time range of $(s + 1, N)$ while X-values would have a time range of $(1, N-s)$.

Figure 5 displays the temporal auto-correlation for ceiling at Washington National Airport, for $s=0$ to 40. The sample data consisted of actual, hourly observations for the months of January and February over a five year period [10].
The graph in Figure 2.5 suggests an exponential decay in ceiling auto-correlation as observations are further apart. Observations taken 30 hours apart or greater have correlation values which are not statistically significant and can be considered approximately independent.

### 2.2.4. Cross-Variable Correlation

Cross-variable correlation, or simply cross-correlation, refers to the correlation between two weather variables at the same site. Cross-correlation is high between sets of airport weather variables. Cross-correlation between ceiling and visibility observations at Boston Logan Airport was calculated for the months of January and February using five years of historical data [3]. The sample cross-correlation coefficient, using the tetrachoric correlation estimator, was 0.83 for Boston.

Because both ceiling and visibility influence an airport's classification, modeling cross-correlation would provide more realistic scenarios for testing and evaluation of air traffic flow management strategies. It would be unrealistic for a model to produce a synthetic ceiling observation of zero feet, while simultaneously generating a favorable observation for visibility.

### 2.3. Sawtooth Wave Model

In this report we present the sawtooth wave model (SWM), a weather model created for the United States Air Force by Boehm [12]. Originally, the SWM was developed to support
wargaming efforts in different regions of the world. This was done by simulating cloud cover ceiling and visibility observations at the sites of interest. This model provided a good foundation and we extended it to produce synthetic wind speed and wind direction. We also incorporated tetrachoric correlation into the model.

2.3.1. Overview of How SWM Works

The heart of the SWM consists of superimposing randomly generated, multidimensional sawtooth waves within a time and space coordinate system [5]. A sawtooth wave, like all other cyclic waves, is characterized by four parameters: wavelength, amplitude, phase shift, and direction. The wavelengths are chosen appropriately as to preserve the spatial temporal and cross-variable correlation values. The amplitude of the sawtooth waves is one for all cases and the phase shift and direction of each wave are chosen randomly. For a detailed description of the sawtooth wave geometry, refer to Hocker [3].

At sites of interest within the coordinate system, the heights of the random waves are summed together. From the Central Limit Theorem, these sums will be approximately normally distributed if a sufficient number of waves (more than 12) are used in the model [11]. These sums are then transformed into standard normally distributed values with a mean of zero and variance of one, i.e., N(0,1).

The N(0,1) values are referred to as Equivalent Normal Deviates, or ENDS [11]. They are also sometimes referred to as z-statistics. The ENDS are converted into observations of weather variables, through a process known as inverse transnormalization. Time-series data are generated by adjusting the sawtooth waves in the time dimension and repeating the process.

2.3.2. Appropriateness of the Sawtooth Wave Model

So why should sawtooth waves be used? By choosing appropriate input values for the sawtooth wave model, the correlational behavior of weather variables can easily be reproduced. Previously from figure 2.4, one can see that the spatial correlation of weather parameters initially exhibit an exponential decay; as distances are further apart the correlation drops exponentially
and even turns negative. The correlation then increases again. Similarly, the SWM exhibits the following correlation behavior [2]. Figure 2.6 illustrates the correlation curve using 4-dimensional and 5-dimensional sawtooth waves:

![Correlation Curves](image)

Figure 2.6: 4-D and 5-D Correlation Curves

Temporal correlation, on the other hand, behaves purely as an exponential decay as shown previously in Figure 2.5. This exponential decay can also be simulated by using sawtooth waves. Instead of having wavelengths that are the same for all of the sawtooth waves as is the case to model spatial correlation, empirical testing shows that using wavelengths in the ratio of 1:2:3:4:5:6:7 for every seven sawtooth waves will produce results with an exponential decay [16]. Although the ratio of wavelengths has been predetermined to produce exponential decay behavior, the initial wavelengths must still be chosen properly—using historical data—to produce the correct time constant of decay. This is done by finding the lag time which produces an auto-correlation of 0.368 or $e^{-1}$. This value is the first temporal wavelength. Subsequent wavelengths are calculated by taking integer multiples of the first wavelength as described above.

### 2.3.3. Implementation

There are seven general steps (see figure 2.7) involved in the current implementation of the SWM to model ceiling, visibility, and wind; these are described in the following subsections.
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Figure 2.7: Implementation Flow Chart
2.3.3.1. Preprocess NOAA Weather Data

Historical weather data is needed for input; we used the NOAA weather data. NOAA weather data comes in two forms: old NOAA weather data as used by Hocker in his implementation of the SWM and new NOAA weather data on CD-ROM. In either case, the data in its raw form cannot be used directly; it must be preprocessed into a usable form. An example of the old weather data for Boston is shown in Table 2-2.

Table 2-2: Old NOAA Weather Data Sample

| C 86 01 01 00046 00046 00046 00046 00080 00055 00120 00050 |
| H 86 01 01 01000 01000 01000 01000 01000 01000 01000 01000 |
| W 86 01 01 22013 22011 23013 24011 25012 25011 26010 27009 |
| C 86 01 02 99999 99999 99999 00070 00065 00065 99999 99999 |
| W 86 01 02 27009 29005 23008 22009 24008 24007 25012 24010 |
| H 86 01 02 01500 01500 01500 01500 01500 01500 01500 01500 |
| W 86 01 03 23008 23008 21008 19007 15005 16006 10009 21007 |
| H 86 01 03 01500 01500 01500 01500 01500 01500 01200 01200 |
| C 86 01 03 00060 00060 00080 00035 00033 00031 00019 00015 |

The first column of data designates the variable observed (C = Cloud Ceiling; H = Horizontal Visibility; W = Wind). The next three columns of data designate the date of the observation in the form of year, month, day. In the actual data, there are 24 columns of data after the date, as opposed to the eight columns shown here, each corresponding to an hourly observation of the weather variable. The ceiling data is given in hundreds of feet and thus the 00046 entry in the first row represents a ceiling of 4600 feet. Horizontal Visibility data is given in hundredths of a mile. Therefore, the 01000 entry in the second row represents a visibility observation of 10 miles; an observation of 99999 represents unlimited visibility. Wind data is given in the form of direction and speed. The first two digits of a wind observation is the direction in tens of degrees and the last three digits provide the magnitude of the wind in knots. The 22013 entry in row three of the data indicates winds from 220 degrees at 13 knots.
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The newer NOAA data is much easier to use and requires less preprocessing than the older NOAA weather data. There is an entry for each hour which lists the wind direction, wind speed, visibility and ceiling. Table 2-3 illustrates how this data might look.

Table 2-3: New NOAA Weather Data Sample

<table>
<thead>
<tr>
<th>Year</th>
<th>Month</th>
<th>Day</th>
<th>Hour</th>
<th>Wind Direction</th>
<th>Wind Speed</th>
<th>Visibility</th>
<th>Ceiling</th>
</tr>
</thead>
<tbody>
<tr>
<td>86</td>
<td>1</td>
<td>11</td>
<td>1</td>
<td>290</td>
<td>5.7</td>
<td>16.1</td>
<td>1310</td>
</tr>
<tr>
<td>86</td>
<td>1</td>
<td>11</td>
<td>2</td>
<td>320</td>
<td>5.2</td>
<td>16.1</td>
<td>1310</td>
</tr>
<tr>
<td>86</td>
<td>1</td>
<td>11</td>
<td>3</td>
<td>350</td>
<td>5.2</td>
<td>16.1</td>
<td>1160</td>
</tr>
</tbody>
</table>

The first four columns of data indicate the time of the observation. For example, the first row of the sample data corresponds to January 11, 1986 with hourly observations ending at 1:00 am. The next four columns give the wind direction in degrees, wind speed in miles per hour, visibility in kilometers, and ceiling height in meters.

The NOAA weather data is first separated by the different weather variables. Cumulative distribution functions (CDFs) are then created for each variable at each site for use in the inverse transnormalization process described later. Also, the spatial and temporal correlation values for each variable as well as the cross-correlation values between variables are calculated.

Additional preprocessing on the wind data is also needed. The NOAA data provides the wind data in the form of wind direction and speed. Correlating wind speed and directions is difficult for two reasons. First, wind speed and wind direction are not independent; there is cross-variable correlation between the two. Second, it is difficult to model circularity of wind direction. For example, there exists a strong correlation between wind blowing at 359° and wind blowing at 0°. We chose to avoid these difficulties by converting the wind vector given by speed and direction into an x-vector (east-west component) and a y-vector (north-south component). Previous studies have shown that these x-vectors and y-vectors are independent and normally distributed random variables[13]. Thus, the PPM can be used to calculate correlation values. To do this, the wind speed and direction data are converted to x- and y-vector values during the preprocessing stage.
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2.3.3.2. Generate Input File

Our implementation of the sawtooth wave model takes as input a file of parameters. A sample input file is given in the appendix. These parameters fall into one of two categories: site parameters and correlation parameters. Site parameters are those parameters that are specific to a site of interest. This includes location, latitude and longitude, as well as cumulative distributions of each of the variables being modeled at each of the sites of interest. Correlation parameters are the inputs that are necessary to assure that the spatial and temporal correlation of the synthetic data is consistent with that of the historical data. These parameters are a reference correlation distance and its corresponding reference correlation, as well as the lag time when the temporal auto-correlation is $1/e$ or 0.368 (the reasoning for this is described in subsection “Calculate Temporal Wavelength”) [22]. For example, if the spatial correlation between sites 400 nm away should be 0.65 then the reference correlation distance is 400 nm and the corresponding reference correlation is 0.65.

2.3.3.3. Calculate Spatial Wavelength

Once the parameters have been read in, the process works as follows. First of all, from the reference correlation distance and its corresponding correlation we can determine the spatial wavelength needed for the SWM as described in Hocker [Hocker]. For instance, suppose we are generating weather along the east coast and two of our sites of interest are LaGuardia Airport and Logan Airport. The distance between New York and Boston is roughly 200 nm. From historical weather data, we have determined that the tetrachoric correlation of cloud ceiling in the two cities is 0.85. This is also true for the tetrachoric correlation of visibility. Our 5-D correlation curve as shown in Figure 2.6 is represented by the following equation derived by Boehm[13]

$$r_5 = 1 - 2.25 \cdot \delta + 1.2 \cdot \delta^2 \quad \forall \delta < 1$$

(2.5)

$r_5$ is the correlation we wish to preserve using the 5-D SWM. $\delta$ is the separation distance between two points in time and space, in units of wavelength. Solving for $\delta$ as a function of correlation, we get
\[ \delta = 0.9375 - \sqrt{0.833 \cdot r_5 + 0.0459} \] \hspace{1cm} (2.6)

For our example where \( r_5 = 0.85 \), we get 0.069 for the value \( \delta \). This means that 200 nm is equal to 0.069 spatial wavelengths and thus we determine that one spatial wavelength is equal to 200/0.069 or 2890 nm.

2.3.3.4. Calculate Temporal Wavelength

The temporal wavelength required by the SWM is derived in a different matter. In fact, it is determined in the preprocessing stage. When looking at the temporal auto-correlation of a weather variable, the time corresponding to the correlation equal to \( 1/e \) or 0.368 is temporal wavelength \( \Lambda_1 \) for the first sawtooth wave. \( \Lambda_2 \) for the second sawtooth wave is twice that of the first; \( \Lambda_3 \) for the third sawtooth wave is three times that of the first and continues as described earlier. With this, we have all of the elements to produce the sawtooth waves.

2.3.3.5. Generate Sawtooth Waves and Sum Heights

Given all of the spatial and temporal wavelengths as well as the x-, y-, and z-coordinates for each site of interest, waves are iteratively generated incrementing the value of \( t \) and randomizing the direction cosines for each wave. Our implementation utilizes a Monte Carlo technique involving a unit hyper-cube, that generates the direction cosines for each wave [14]. For example, in generating two data points using 14 waves each, one would have random direction cosines for each of the 28 different waves. The value of \( t \) for the first 14 waves would be 0 and for the second 14 waves would be 1. The spatial wavelength would be the same for all 28 waves and the temporal wavelength changes in the ratio of 1:2:3:4:5:6:7 every seven waves. From this, we calculate the sum of sawtooth wave heights at each site of interest at each time point and subsequently calculate the ENDS.

2.3.3.6. Inverse Transnormalization

The final step is transforming the ENDS into raw synthetic observations and forecasts using the process of inverse transnormalization. The first step in inverse transnormalizing an
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END, is determining the normal cumulative probability from $-\infty$ to the END value according to the standard normal distribution, i.e., $N(0,1)$. In other words, the $z$-statistic must be transformed to a cumulative probability. For its facility in implementation, a polynomial approximation from the Handbook of Mathematical Functions was employed to get the cumulative probabilities.

Next, referencing the input CDFs for each variable, the cumulative probabilities are converted into raw weather observations. For example, assume our sawtooth wave sum for synthetically producing ceiling data is 5.84 as in Table 2-4. The END is then calculated to be -1.074. From this, we gather that the normal cumulative probability corresponding to a $z$-value of -1.074 is 0.141. We then go to the ceiling cumulative distribution function and find the ceiling value that corresponds to a cumulative probability of 0.141.

<table>
<thead>
<tr>
<th>$w_{BOS}$</th>
<th>$z_{BOS}$</th>
<th>$P(Z &lt; z_{BOS})$</th>
<th>$c_{BOS}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.84</td>
<td>-1.074</td>
<td>0.141</td>
<td>1916 ft</td>
</tr>
</tbody>
</table>

Because the CDFs are computed based on discrete thresholds, it is necessary to use linear approximations in between the thresholds, in order to complete the continuous functions.

2.3.3.7. Postprocess Synthetic Output

Before using the synthetically generated values immediately, some minor postprocessing is done. The wind values produced by the SWM are still in terms of x-vectors and y-vectors. These values are changed back to speed and direction so that data is in the NOAA format. This allows applications designed to use NOAA data to use the synthetic data without further processing.

Also, the lags that were calculated for the temporal correlation need to be incorporated into the data. This is done by “slipping” the data to meet the lag requirement. For example, suppose 1000 data points were produced for Boston and New York and that the lag between the
two sites was determined to be 4. This means that weather values produced at time 0 synthetically can represent time 0 for New York but represent time 4 for Boston. We do this for all times for which the data was produced and write to output files accordingly.

2.4. Weather Generation Results

The SWM was used to generate synthetic weather observations at Boston’s Logan International (BOS), New York’s LaGuardia (LGA), and Washington D.C.’s National (DCA) airports. The separation distance between BOS and LGA of 160.06 nautical miles and corresponding correlation values of 0.76 for ceiling and visibility, 0.71 for x-vectors, and 0.74 for y-vectors were used as the reference correlation distance and reference correlation values, respectively, as inputs to the SWM.

The resulting weather observations supported the validity of the SWM as an accurate weather model. The correlation values of the synthetically generated weather data were calculated in the same manner as they were for the historical weather data. In most cases, these correlation values were identical or very close. Consider, for example, the correlation between x-vector values at the three airports. The input given to the SWM for x-vectors was the correlation of 0.71 between BOS and LGA. The synthetic weather data produced a correlation of 0.75 between the two sites. Similarly, the historical data also shows that the correlation between x-vectors at BOS and those at DCA is 0.52 while the synthetic weather data indicates a correlation level of 0.51. The largest difference exists for correlation data between LGA and DCA where the historical data indicates a correlation of 0.61 but the synthetic data resulted in a correlation of 0.71.

For purposes of the air traffic control simulation testbed, this accuracy is sufficient.

2.5. Regional Coverage Constraint

The accuracy of the SWM is only good for a single region. Different regions have different climate conditions and thus using one reference correlation, or one sawtooth wave model for that matter, to generate weather for a large area such as the United States would not be extremely accurate.
How does one produce accurate synthetic weather observations and solve the problem of regionality? There are two techniques to compensate for the problem. The first technique is to use the "breathing earth" model described in Hocker. In essence, the radius of the Earth is changed to preserve different sets of correlation values. For example, consider two sites $S_1$ and $S_2$ which are $D_1$ nautical miles apart and have a spatial correlation $R$. Next, consider another site $S_3$ that also has a spatial correlation $R$ with site $S_1$ but is $D_2$ nautical miles apart. Generate observations for $S_1$ and $S_2$ as normal. To generate observations for site $S_3$, reduce the value for the radius of the earth so that the distance between $S_1$ and $S_3$ is $D_1$ nautical miles and proceed as normal. This concept of the "breathing earth" works by varying the effective radius of the earth so that locations will have the required distance between them to get the desired correlation. These techniques can be used to achieve desired correlation values between any pair of sites.

Another approach to the problem is to use two or more sawtooth wave generators which are sufficiently far apart that they would be considered independent and using weighted values to generate observations for sites in between. For example, suppose one wanted to generate weather observations for BOS, LGA, DCA, Chicago’s O’Hare International Airport (ORD), Minneapolis-St.Paul International Airport (MSP), and Pittsburgh International Airport (PIT). One sawtooth wave generator, call it the east coast generator, can be used to produce weather observations for BOS, LGA, and DCA. Another sawtooth wave generator, call it the north central generator, can be used to produce weather observations for ORD and MSP. These two generators can be considered independent because of the distance between ORD and the three east coast airports. Observations at PIT can be generated from the east coast generator but because of the distance between PIT and the three east coast airports, the observation may not be completely accurate. Similarly, observations for PIT can be generated by the north central generator but accuracy problems may also arise. A compromise can be made by weighting observations from the east coast generator and observations from the north central generator dependent on the correlation between PIT and sites in the two regions. Summing these two observation values should produce a more accurate observation.
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2.6. Conclusion

In conclusion, the SWM is a statistical weather model that is appropriate for use in air traffic flow simulations. With this model, we can generate synthetic weather variables that preserve the spatial correlation among sites, the temporal auto-correlation inherent in weather, and the cross-variable correlation between weather variables such as cloud ceiling and visibility. The model is based on historical weather data at the various sites of interest but historical data at all sites is not essential. For example, if we were attempting to generate weather synthetically at Boston, New York, and Washington, DC but only had weather data for Boston and Washington, we could still generate weather in New York. The sawtooth wave sums would come from the sawtooth waves generated based on data from Boston and Washington. For cumulative distribution functions for New York, one may use an average of cumulative distribution functions for Washington and Boston.

One must, however, use discretion when using the SWM. The SWM should be used for a local region. Using one SWM to generate weather for the entire United States is not advised. When the region is not localized, the homogeneity of spatial and temporal correlation is lost and the SWM loses accuracy. If one is trying to generate weather across the United States, the "breathing earth" model or multiple SWMs should be used.

The SWM's properties that make it appealing for use in air traffic control flow management research are simplicity and flexibility.
3. Airport Capacity Modeling

To develop an effective ATFM strategy, it is essential to have reliable and accurate values for airport capacity. In the past, these capacity values were simply the maximum number of arrivals that a particular airport could accommodate depending on the weather or meteorological conditions at the time and the runway configuration being used. Arrivals were considered to be the bottleneck of the system and the main reason for delays. It was assumed that departures could be inserted whenever needed and thus only arrival capacities were desired. As air traffic demands have increased and with airlines using hubs and flight banks, the demand for departure capacity has also become significant. For this reason, it is important to consider not only the arrival capacity of an airport but also the departure capacity as well as the interaction or tradeoff between the two in implementing effective strategic flow management programs.

In this chapter, we will introduce and compare four models that have been used to model airport capacity. From this point, whenever the word capacity is used it will refer to the total (both arrival and departure) capacity unless specified otherwise.

3.1. Empirical Data Capacity Frontiers

The first model to be introduced is one developed by Eugene Gilbo under the FAA’s Advanced Traffic Management System (ATMS) program [15]. Because this approach uses historical counts of arrivals and departures, the capacity estimates from this model are both realizable and easy to estimate.

3.1.1. Inputs

The inputs needed to get empirical data capacity frontiers (EDCFs) are historical counts of arrivals and departures at an airport along with the associated meteorological conditions and runway configurations. Data should be taken for consecutive time intervals over a long period of time. For each time interval, the number of arrivals, the number of departures, the meteorological
Chapter 3: Airport Capacity Modeling

conditions (i.e. VFR or Visual Flight Rules) and runway configuration should be noted. For example, sample data might look like:

<table>
<thead>
<tr>
<th>Time</th>
<th>Arrivals</th>
<th>Departures</th>
<th>Meteorological Conditions</th>
<th>Runway Configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1/96 15:00</td>
<td>9</td>
<td>7</td>
<td>VFR1</td>
<td>2</td>
</tr>
<tr>
<td>1/1/96 15:15</td>
<td>10</td>
<td>7</td>
<td>VFR1</td>
<td>2</td>
</tr>
<tr>
<td>1/1/96 15:30</td>
<td>6</td>
<td>6</td>
<td>VFR2</td>
<td>3</td>
</tr>
</tbody>
</table>

In the sample data, counts were taken every fifteen minutes. During the first fifteen-minute interval which ended at 3:00 PM the arrival count was 9 and the departure count was 7. These can be standardized to arrival rates and departure rates of 36 per hour and 28 per hour respectively. Also, during the 3:15-3:30 PM interval there was a configuration change as well as a change in meteorological conditions.

3.1.2. EDCF Estimation Method

Gilbo states that it has been established that arrival and departure capacities are connected with each other through a convex, nonlinear functional relationship [15] and this is supported by Newell [16] and Swedish [17]. Assuming the validity of this statement, an EDCF is easily estimated given the historical arrival and departure counts over a long period of time.

Gilbo’s method assumes that during the period of time considered, the observed peak arrival and departure counts reflect the airport performance at or near the airport’s capacity. This seems to be a reasonable assumption for pacing airports considering that they are known to experience congestion and delay during peak hours. This congestion and delay is an indication that these airports operate close to or near their capacity limits. We can then consider that curves that envelope these peak departure and arrival counts are valid airport capacity estimates.

Because capacity calculations are derived for a given runway configuration and meteorological condition, the data needs to be organized by these operation conditions. Each airport has a set of runway configurations that are used with enough frequency that empirical
data can be collected to estimate curves for it. For each of these runways the weather conditions are generally grouped into the four categories described in the previous chapter based on ceiling and visibility: VFR1, VFR2, IFR1, and IFR2. Configuration curves are then derived for each configuration and weather condition.

To extract an EDCF from a set of historical counts for a given configuration and meteorological condition, first plot every data point on a graph with the horizontal axis being arrivals and the vertical axis being departures as shown in Figure 3.1.

![Figure 3.1: Historical Counts of Hourly Arrivals and Departures](image)

After plotting the historical counts, a piecewise-linear concave curve is stretched around the set of points to form a convex set of feasible operating points. The following figures show how this is done using the sample data in Figure 3.1.
Chapter 3: Airport Capacity Modeling

Algorithmically, to develop these curves, one starts with a line of slope equal to zero and connects the point with the greatest number of departures to the vertical axis. This is the first piece of the EDCF as shown in the first part of Figure 3.2. The data point which lies on this line and also has the greatest number of arrivals becomes the pivot point for the next piece of the frontier. From the pivot point, one gradually decreases the slope of the line until another data point is hit. Again, the data point that lies on this line with the greatest arrivals becomes the next pivot point. This process continues until the slope of the line is undefined because there are no more observations with arrivals greater than the last pivot point and then the final piece is drawn by connecting the last pivot point to the arrivals axis.

This method is extremely sensitive to possible outliers in the data. For example, suppose there was one data point that showed 100 arrivals per hour and 30 departures per hour but all other data did not have arrivals per hour value greater than 60. One would suspect that this data...
point may have been miscalculated or merely a unique occurrence when the airport operates beyond its normal capacity limits for a short period of time. For all practicality, this data point is not very useful to us and should not be used for generating EDCFs.

To mitigate the sensitivity to outliers, capacity estimates should be made after rejecting some extreme observations. To do this, one can use only data points that occur at least twice or three times. If a data point occurs more than once or twice, it is reasonable to assume that the data point represents a capacity at which the airport can operate.

Using this rejection criterion does pose one problem. Longer time intervals generally mean more data points are needed and much more time is needed to collect data. For example, suppose one was collecting data in hourly intervals. Arrival and departure data of (45 arrivals, 35 departures) and (46 arrivals, 37 departures) may be collected. Suppose another person collects data in fifteen minute intervals. Values such as (11 arrivals, 9 departures) and (11 arrivals, 9 departures) may be recorded. The person collecting data in hourly intervals may be getting very detailed data; however, because the data is so finely grained many observations will be needed to get multiple occurrences of the data. On the other hand, the person collecting data every fifteen minutes may be getting less detailed hourly data, getting more observations in a one hour period, and should be getting more multiple occurrences than the person taking data hourly.

One way to validate the rejection criterion used for deriving the curves is to give the percentage of data used when using the rejection criterion. A good rejection criterion will still use 90% of the original data [23]. For all of these reasons, the curves derived for this thesis used data taken in fifteen minute intervals and used only data points that occurred at least twice.

3.2. Engineered Performance Standards

The idea of Engineered Performance Standards (EPSs) was introduced in early 1974 in an effort undertaken by the Operations Research Branch of the Executive Staff, Air Traffic Service to develop a system for measuring performance of major airports. Previous to this effort, the only indicators of an airport’s performance were delay statistics maintained by airlines [18]. The problem with the use of delays is that these statistics give no indication of how well an airport
Chapter 3: Airport Capacity Modeling

performed relative to how well it should have performed. Therefore, EPSs were developed which predict how an airport should perform in operations per hour or capacity level given that there is sufficient demand.

3.2.1. Background

EPSs, like the EDCFs, are set for each runway configuration and weather condition. Weather is defined into the four weather categories described in the EDCF section. The exact values of ceiling and visibility that define the weather categories are different for each airport but in general they are defined in the following manner. VFR1 conditions occur when the cloud ceiling is at least 1000 feet above the tallest structure in the vicinity of the airport and a visibility of at least five miles. For example, in Boston the tallest structure near Logan Airport is either the Hancock Building or the Prudential Tower. The approximate height of these buildings is roughly 1000 feet and therefore Logan operates under VFR1 conditions when the cloud ceiling is greater than 2500 feet and visibility is greater than 5 miles. For VFR2 conditions, the cloud ceiling must be greater than 1000 feet and the visibility must be greater than 3 miles. Below either of these minimums it is considered IFR conditions. The distinction between IFR1 and IFR2 conditions are runway dependent. Certain runways are equipped with special landing equipment that enables aircraft with special landing equipment to land given certain conditions [21].

3.2.2. Calculation Methods

Developing EPSs for an airport is a three step process. Initially, a theoretical capacity is calculated for each configuration and weather condition. A configuration is not only the set of runways that will be used but also specification of which operations will be performed on each of the runways. In other words a runway in a configuration must be designated as use for arrival, departure, or mixed operations. Also, the availability of smaller side runways must be provided. Next, this theoretical capacity is compared with facility capacity opinions such as those of air traffic flow managers or air traffic controllers at the airport in order to evaluate the validity of the theoretical capacity and also to evaluate any local unique operating conditions. Finally, EPSs are derived for each configuration and weather condition [18].
3.2.2.1. Calculating Theoretical Capacity

The first step in producing EPSs for an airport is to develop the theoretical capacity for each runway configuration and weather condition. To do this, four things are assumed. First, there is an uninterrupted flow of traffic; second, spacing is ideal based on minimum in-trail separation requirements; third, hourly arrivals and departures are balanced; and fourth, an overall traffic profile reflects the proportion of different aircraft type seen each hour.

The sequence of the aircraft is considered random with each aircraft operation independent of the preceding operation. The service time for each aircraft is constrained by the type of operation (arrival vs. departure) as well as the previous aircraft’s speed and size (heavy vs. non-heavy). Heavy aircraft are those that are over 300000 pounds and include Boeing 747s and DC-10s. The time that each aircraft is constrained by the previous user is called the “restraint time” for the pair of aircraft. These restraint times can be about 150 seconds for a heavy aircraft arrival followed by a non-heavy aircraft arrival and as short as 45 seconds for a non-heavy arrival followed by a non-heavy departure. A “restraint time” is then set for all possible sequences of aircraft size and operation type. Using the overall traffic profile the probability of occurrence for each sequence can be calculated and used to find the expected value or average “restraint time.” From this, a theoretical capacity standard can be calculated.

For example, suppose that the mix of aircraft at a particular airport was 10% heavy jets and 90% non-heavy aircraft. The probability of a heavy jet demanding airport resources followed by a non-heavy aircraft demanding airport resources is 0.1 times 0.9 or 0.09. Similarly, because we assume balanced hourly arrivals and departures, the probability of an arrival followed by an arrival is 0.5 times 0.5 or 0.25. Multiplying these values together would result in the probability of 0.0225 for a heavy jet arrival followed by a non-heavy aircraft arrival. This type of calculation can be made for each sequence of aircraft size and operation type. To get the average “restraint time,” we multiply the probability of each runway sequence occurrence times its corresponding “restraint time” and sum them for all possible sequences. To get the theoretical capacity for the configuration, we take the reciprocal of the average “restraint time.” For instance, if the average restraint time was calculated to be 45 seconds then the capacity would be
1 operation per 45 seconds or multiplying by 3600 seconds per hour, we get a capacity of 80 operations per hour.

### 3.2.2.2. Comparison of Ideal Capacity with Facility Opinion

For each frequently used configuration and weather condition at an airport, a facility opinion was solicited to validate the theoretical capacities. These opinions also provided insight for calibrating theoretical capacities between facilities having like conditions. Although these opinions were not used in the actual EPS calculations, they provided a starting point for discussing airport capacity. There were some differences that could be attributed to the difference in methods used by different facilities. Some facility managers are more likely to use rounded estimates as opposed to discrete mathematical values from analytical models. Also, the theoretical models assume an ideal user and controller whereas the facility opinion takes into account the error in visual spacing. Overall, the facility opinions were generally somewhere from six to eight percent below that produced by the theoretical model [18].

### 3.2.2.3. Derivation of EPSs

The facility opinions, although not used directly in the calculation of the EPSs, are indirectly used because they occasionally explain differences between theoretical capacity values and realized values. For example, facility opinion values imply that there is a greater separation between succeeding aircraft than the ideal miles-in-trail values used for theoretical calculations. It was found that the separations between heavy/heavy’s and non-heavy/heavy’s of four and five nautical miles respectively was consistently maintained by air traffic controllers during periods of high demand. The separation between non-heavy/non-heavy’s of three nautical miles, however, was found to be actually maintained somewhere between three and four nautical miles. Therefore, by using a separation distance of 3.5 instead of three nautical miles (or approximately a fifteen second increase in “restraint time”) the numbers for capacity seemed more consistent with facility opinions. These values were then used as EPSs.

Also, for some facilities the assumption that there are balanced arrivals and departures was dropped. Admittedly, by the conservation of aircraft, on average there is a 50-50
arrival/departure mix. During peak periods when the demand rate exceeds or is near capacity, this is not always true. Therefore, some of the EPS numbers are derived from other arrival/departure ratios.

3.3. FAA Airfield Capacity Model

The FAA Airfield Capacity Model (FAAACM) is a model that was originally developed in the 1970s by a consortium including Peat, Marwick, Mitchell, and Company and McDonnell Douglas Automation. It was later modified by the Systems Research and Development Service (SRDS) branch of the FAA. A major effort was initiated to upgrade the SRDS version to add new functions and abilities as well as incorporate the current ATC procedures. This was completed in 1981 and this is the version that will be referred to as the FAAACM [17].

3.3.1. Overview

The FAAACM is a model designed to calculate the maximum throughput capacity of a runway system assuming a continuous flow of demand. Initially, the arrival-only capacity is calculated by determining the minimum time between successive arrivals and inverting this time to get the maximum number of arrivals in an hour. Next, the maximum number of departures which can be inserted into the arrival stream is calculated. This gives the arrival-priority capacity. Similarly, one can calculate the departure-priority capacity by inserting arrivals into a departure stream. When a specific ratio of arrivals to departures is desired, the desired capacity is achieved by either dropping excess arrivals or departures or by interpolating between the arrival priority and departure priority points. The details of these capacity calculations as well as the inputs needed will be discussed in subsequent subsections.

3.3.2. Capacity Calculations

The premise behind the FAAACM is that all runway configurations are a combination of four fundamental configurations: single runway, closely spaced parallel runways, intermediate spaced parallel runways, and intersecting runways.
3.3.2.1. Single Runway

Calculating the capacity of a single runway with arrivals only is straightforward. The hourly capacity is given by

\[
\text{CAPACITY} = \frac{3600}{\text{TAA}}
\]  

(3.1)

where TAA is the average time separation in seconds between successive arrivals. To calculate TAA the required time separation for each aircraft class pair (TAA\((i,j)\)) is determined by taking the larger of the arrival runway occupancy time of lead aircraft \(i\) and the airborne time separation for aircraft pair \(ij\). The arrival runway occupancy time is the duration of time between when the lead aircraft crosses the runway threshold and when it exits the runway. The airborne separation time is duration of time between when the lead aircraft crosses the threshold and when the trailing aircraft crosses the threshold maintaining the minimum in-trail separation requirement.

![Arrival Runway Diagram](image)

*Figure 3.3: Arrival Runway Diagram*

There are four aircraft classes to consider in the FAAACM and they are defined by their maximum take-off weight (MTOW). The small aircraft class is defined as those aircraft with a MTOW of less than 12500 lbs. These are mostly general aviation aircraft. The aircraft class
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labeled as medium-sized aircraft have a MTOW between 12500 and 350000 lbs. with the exception of the Boeing 757. Even though the MTOW of the 757 is within the medium-sized aircraft range, due to its wingspan and wake vortices produced, the 757 is categorized in the large-sized aircraft class. Aircraft that are included in the medium category are Boeing 727s and 737s as well as the DC-9. Aircraft with a MTOW greater than 350000 lbs. comprise the heavy aircraft class. These include A340s, DC-10s, L1011s and 747s [24]. An example of an aircraft pair is heavy followed by medium.

To calculate the airborne time separation for an aircraft pair \( ij \), two cases must be considered. These two cases are shown in Figure 3.4.

![Diagram of Opening and Closing Airborne Separations](image)

**Figure 3.4: Opening and Closing Airborne Separations**

The first case is the closing case where the velocity of the lead aircraft \( i \) is less than the velocity of the trailing aircraft \( j \). In this situation, the minimum in-trail separation requirement is reached when the lead aircraft is at the threshold of the runway. Thus, the airborne separation time is equal to the time it takes the trailing aircraft to cover the minimum in-trail separation. In other words, it is equal to the minimal in-trail separation distance divided by the velocity of the trailing aircraft \( j \). The second case is the opening case where the velocity of the lead aircraft \( i \) is greater than the velocity of the trailing aircraft \( j \). In this case, the minimum in-trail separation requirement is reached when the lead aircraft \( i \) enters the common approach path; the distance between the two aircraft will increase as they fly along the common approach path. The airborne
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separation time is then the time for the trailing aircraft \( j \) to reach the threshold (the distance of the common approach path plus the in-trail separation requirement divided by the velocity of aircraft \( j \)) minus the time for lead aircraft \( i \) to reach the threshold (the distance of the common approach path divided by the velocity of lead aircraft \( i \)) [19].

Once \( \bar{TAA}(i,j) \) is calculated for each aircraft pair, the average required time separation is calculated by weighting each of these times with the frequency of occurrence for each pair. This frequency is assumed to be the product of the frequency of the mixes of the aircraft involved. For example, if the fleet mix at a particular airport consisted of 10% heavy aircraft and 60% medium-size aircraft, then the frequency of a heavy aircraft arrival followed by a medium-sized aircraft would be \((0.1) \times (0.6)\) or 0.06. Therefore, the average required separation is determined:

\[
TAA = \sum_i \sum_j \bar{TAA}(i,j) \times \text{freq}(i) \times \text{freq}(j)
\]

(3.2)

Similarly, when calculating capacity for a single runway with departures only, the same process is used. Instead of using arrival runway occupancy times and miles-in-trail separations, departure runway occupancy times and departure threshold separations.

For mixed operations, the capacity is calculated by taking the arrivals only capacity and inserting departures between arrivals. There are three requirements that need to be considered when inserting departures. First, only one aircraft can occupy a runway at any given time. This means that a departure cannot start its takeoff roll if an arrival is on the runway. Second, a departure must be able to clear a runway before the next arrival. Therefore, a departure cannot roll if an arrival is within some specified distance of the runway threshold. Finally, departure separations must still be met if inserting multiple departures between an arrival pair [17]. Using these three conditions, the probability of inserting departures between each arrival pair is calculated. The departure capacity is computed from these probabilities and the aircraft fleet mix.
3.3.2.2. Closely Spaced Parallel Runways

Closely spaced parallel runways are those parallel runways that have a centerline separation of less than 2500 feet. Under VFR conditions, simultaneous landings can occur on these runways unless one of the jets is a heavy aircraft. When this is the case, the runways become dependent and the trailing aircraft on both runways must observe the single runway miles in-trail separation distance because of the large wake turbulence caused by heavy aircraft. Under IFR conditions, the parallel runways are dependent; however, there is still an advantage of having two runways if one is used for arrivals and the other for departures. While it still holds that a departure cannot be released if an arrival is within some specified distance from the threshold of the runways, it may be released as soon as the arrival touches down on its runway. By using the separate runway for departures the rule that there is only one aircraft occupying a runway is not violated and departures can occur more rapidly.

3.3.2.3. Intermediate Spaced Parallel Runways

Intermediate spaced parallel runways are those which have centerline separations between 2500 and 4300 feet. Parallel runways with centerline separations greater than 4300 feet are considered to be independent under all weather conditions and are treated as two single runway cases. For intermediate spaced parallel runways, the runways are considered to be independent, regardless of aircraft size when the conditions are VFR and simultaneous approaches can be made. Under IFR conditions, however, the runways are dependent and simultaneous arrival approaches cannot be made. The difference between intermediate spaced parallel runways and closely-spaced parallel runways under IFR conditions is that the centerline separation is large enough that cross track wake turbulence does not add to the required arrival separation distances. What this means is that a 3.0 nautical mile in-trail separation is all that is needed for aircraft on different runways. Under closely spaced parallel runways the separation could be as large as 6.0 nautical miles if a small aircraft is trailing a heavy aircraft for arrivals on different runways.

A change was made in the ATC procedures during the early 1980s for runways that have centerline separations between 3000 and 4300 feet. The change allows alternating arrivals on intermediate spaced parallel runways to be run using a 2.0 nautical mile diagonal separation.
instead of the 3.0 in-trail separation [17]. This allows for decreased interarrival times and greater capacity.

### 3.3.2.4. Intersecting Runways

The logic for capacity calculations for intersecting runways is similar to that for parallel runways except that the point of intersection introduces some new constraints. The probability of inserting departures into the interarrival gap is dependent on three conditions. First, it is subject to the time for an arrival to clear the intersection. Second, there exists a required separation between a departure crossing the intersection and an arrival or departure on the other runway. Finally, there still exists a required separation between departures on the same runway. Also, if the flight paths of arrivals and departures are projected to cross, there is an additional wake turbulence separation that must be considered.

Details of calculating capacities for closely spaced parallel runways, intermediate spaced parallel runways, and intersecting runways, can be found in [17].

### 3.3.3. Inputs to the FAAACM

Several inputs are needed to use the FAAACM. First, the configuration being used is specified. This includes which runways are being used, what type of operations occur on each of these runways and what the fleet mixes are for each of the runways. For each arrival runway, an average arrival runway occupancy time is required. Because smaller aircraft have shorter runway occupancy times, these average arrival occupancy times need to be specified for each type of aircraft.

Besides runway specific inputs, some general information must also be supplied by the user. This includes the list of minimum arrival separation distances for each aircraft pair, the minimum departure separation times for each aircraft pair, the final approach speeds of the different aircraft types and the length of the final approach path for each aircraft. Also, average departure runway occupancy times are required as inputs but are not runway specific. The same
occupancy time is used for each departing runway. Weather inputs such as ceiling and visibility are used to determine the flight rule conditions.

The FAAACM is not a deterministic model. Some quantities are modeled stochastically and means and standard deviations are used as inputs, e.g., arrival runway occupancy time, interarrival time, and departure runway occupancy time. Along with these, a probability of violation for all stochastic variations is specified. Suppose the probability of violation for runway occupancy time is 0.05. Runway occupancy time is a random variable and thus has a probability density distribution. The probability of violation of 0.05 corresponds to the threshold value that has a cumulative distribution of 0.95 or 1.00 - 0.05. This means that only 5% of all runway occupancy times will be greater than the value corresponding to 0.05 probability of violation. Obviously, the smaller the probability of violation one specifies, the greater the threshold value.

For certain models, some additional input data is needed. For example, in the case of configurations that include intersecting runways, the average time for aircraft to clear the intersection as well as standard deviations of these times are also needed.

Finally, the user is able to specify different arrival/departure ratios. To produce capacity frontiers using the FAAACM, increments of 10% were used to get 11 different capacity frontier points ranging from (100% arrivals, 0% departures) to (0% arrivals, 100% departures).

3.4. LMI Airfield Capacity Model

The Logistics Management Institute (LMI) is an FFRDC (Federally Funded Research and Development Center) located in McLean, Virginia tasked to analyze the benefits of systems developed in the NASA Terminal Area Productivity (TAP) Program [20]. This was done by taking airport-specific data, estimating an airport’s capacity, using a queuing model to calculate aircraft delay, and subsequently calculating the cost savings to airlines by reducing delay using some or all of the TAP systems. For the purposes of this study, the primary interest lies in the models for determining an airport’s capacity.
3.4.1. Overview

The LMI Airfield Capacity Model (LMIACM) was developed as a result of an unsuccessful search for an appropriate capacity model that is a function of various parameters including weather, air traffic control procedures, and the technology available [20]. For the benefits analysis that LMI was conducting, a decision was made to use an analytical model instead of a simulation. An analytical model can require more initial overhead in collecting of highly detailed airport-specific data on airport operations to calibrate and validate the model but only a single execution of the model is necessary. Often, the run time of the single execution is faster than a single simulation run. With simulations, multiple runs are often needed and a highly detailed description of all aspects of airport operations may be required as well. Because LMI was specifically studying two airports, Boston’s Logan International and Detroit’s Wayne County, using an analytical model was a logical choice.

The challenge of developing an analytical model was to determine which parameters should be incorporated into the model to reflect the impacts of new procedures and new technology. Previous models, namely the FAAACM, used parameters such as miles-in-trail separation requirements, aircraft approach velocities, runway occupancy times, aircraft fleet mix, and standard deviation of interarrival times. For this reason, the FAAACM was thoroughly evaluated to see if it was suitable for LMI’s study.

3.4.2. FAAACM vs. LMIACM

It was found that while the FAAACM was suitable for some analysis needed for the LMI study, it was deficient in one specific area that required development of the LMIACM. LMI needed the ability to model the effects of technological advances brought about by various phases of the TAP program. The FAAACM lacks this capability. For example, technologies provided by the TAP program will allow pilots and controllers to reduce separation distances and improve the predictability of the spacing between successive arrivals. The FAAACM assumes that the distribution of interarrival times is normal and the best way to model this technological advance would be to reduce the mean and standard deviation of the interarrival time. LMI was not comfortable with assumption of a normal distribution for interarrival times and felt
that this approach would yield inaccurate results [25]. Instead, LMI felt it necessary to rigorously derive the distribution of interarrival times and thus developed their own model the LMIACM. The LMIACM, formally estimates the distribution of interarrival times using the aircraft fleet mix and the additional parameters of the mean and standard deviation of approach speed, the standard deviation of the wind speed, and the standard deviation of aircraft position uncertainty. The standard deviations determine the variance in interarrival times and the shape of the distribution for different pairs of aircraft while the fleet mix determines the frequency that each aircraft pair occurs.

Other technological advances such as improved availability of information to controllers and faster communication between pilots and controllers are also difficult to incorporate into the FAAACM. The LMIACM takes a controller-based view of airport operations and thus parameters such as quality of information accessible to air traffic controllers, including aircraft position and speed as well as delays in communication are parameterized and can properly be used to estimate airport capacity.

3.4.3. Specific to an Airport

The LMIACM also differs from the FAAACM in that it is specific to an airport and not as generic as the FAAACM. Instead of calculating capacities for a type of configuration, such as intersecting runways, the LMIACM calculates capacities for each runway configuration at an airport. After talking to the air traffic controllers at the airports of interest, LMI was able to gather airport specific data allowing them to calibrate their model to produce accurate capacity results. For example, at Boston’s Logan International, a frequently used configuration involves runways 4L and 4R for mixed operations and runway 9 for departures, as depicted below.
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Instead of analytically determining the departure capacity of runway 9 due to constraints at the intersection, LMI consulted with air traffic controllers and determined that the departure capacity is reduced to 80% of the capacity if the runways did not intersect. This type of modeling requires a separate model for each airport of interest [25].

An analysis of the capacity values produced from these different models follows in the next chapter.
4. Results and Analysis

One objective of this thesis is to compare and evaluate the four different capacity models. To do this, a simulation using the different capacity models was implemented and the results were analyzed.

Figure 4.1 above illustrates the simulation process used to obtain the results discussed in this chapter. The inputs to the simulation are weather observations at the airports of interest. These observations can either be historical weather data or weather synthetically generated using the sawtooth wave model described in chapter 2. From the ceiling and visibility observations and the flight rule constraints for the airport of interest, the flight rule conditions are determined. From the wind observations, a list of active runways (runways which do not violate the maximum crosswind constraint) is generated; subsequently, a list of possible configurations using only active runways is produced. A capacity model is used to derive capacity frontiers for all
combinations of configurations and flight rule conditions. These frontiers, the flight rule conditions, the list of possible runway configurations, as well as an operating point criterion are inputs to a configuration chooser.

The configuration chooser outputs the configuration that best meets the operating point criterion. We used the maximum operations rate as the operating point criterion. Therefore, the configuration chooser calculates the maximum operations rate from each capacity frontier corresponding to an active configuration and current flight rule conditions. Then the configuration with the maximum of these operations rates is chosen as the best configuration.

The chapter is organized into four sections. The first section describes the different results obtained from the simulation runs. The second section analyzes the results of the simulation runs by specific airport characteristics. The third section identifies the strengths and weaknesses of the different capacity models described in the previous chapter. These strengths and weaknesses will be the basis for the recommendation made in the final section.

### 4.1. Simulation Results

The configuration choices and corresponding capacities produced by the simulation were analyzed in order to evaluate the accuracy of the different capacity models and identify flaws in the simulation process. To do this, three results were examined closely: configuration usage, capacity coverage, and capacity time series data. Configuration usage summarizes the percentage of time each of the different configurations for an airport is chosen. Capacity coverage illustrates how much capacity is available at an airport. Time series data is used to depict how capacity of an airport changes over time.

Data was not available to implement all four capacity models for a single airport but three airports had sufficient data to implement three of the models. EPS data was available for all of the pacing airports and the FAAACM could be used for any of the airports. On the other hand, historical counts for the data-intensive EDCF model were only available for EWR and LGA. For the LMI model, only BOS was examined in this simulation. Results from these airports, BOS, EWR, and LGA, will be the focus of this section.
The results in this section were produced with some caveats in mind. The simulation assumes that only weather effects the capacity of an airport. We understand that there are other factors which affect an airport's capacity such as airport maintenance and noise restriction but these are not incorporated into the model. We also assume that the maximum crosswind allowed for a runway is 15 knots. As stated in chapter 2, this may vary but generally 15 knots is the maximum crosswind allowed. All results and analysis is based on weather data for January and February over a five-year period (1986-1990) except for BOS to limit the effects of seasonality. For BOS, seasonal effects were examined using weather data for all of 1990.

4.1.1. Configuration Usage

Configuration usage is the distribution of configuration choices made by the simulation using the operating point criterion. The configuration usage distributions for the different models were examined for each of the three airports. For BOS, the configuration usage distribution diagrams were identical for the different models as illustrated below. A table of configuration numbers and a description of the configurations they refer to can be found in Appendix B.

![BOS Configuration Usage](image)

*Figure 4.2: BOS Configuration Usage Distributions*

This type of result implies that the capacity values of the different configurations relative to each other are the same for the different models (EPS, FAA, and LMI).
Table 4-1: BOS Configurations Sorted by Capacity Under VFR1 Conditions

<table>
<thead>
<tr>
<th>EPS Configuration</th>
<th>EPS Capacity</th>
<th>FAA Configuration</th>
<th>FAA Capacity</th>
<th>LMI Configuration</th>
<th>LMI Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>110</td>
<td>1</td>
<td>111</td>
<td>1</td>
<td>147</td>
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<tr>
<td>2</td>
<td>106</td>
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<td>57</td>
<td>10</td>
<td>58</td>
</tr>
</tbody>
</table>

Table 4-1 illustrates that the rank order of the capacities of the configurations at BOS in VFR1 weather are the same independent of the model used. As described earlier, the wind determines whether a configuration is active or not. This is independent of the capacity model being used and thus if a configuration is active when using EPS values, the configuration is active using FAA and LMI values as well. Because the rank order of the configurations and the list of possible active configurations are the same across the different capacity models, regardless of which capacity model is used, the same configuration is chosen by the configuration chooser.

EWR configuration usage data is similar to that of BOS in that the usage is identical for the EPS and FAA capacity models. There are, however, two characteristics that are magnified in the case of EWR. These characteristics are the dominance and equivalence of configurations. Consider the configuration usage distribution below in Figure 4.3:
Chapter 4: Results and Analysis

Figure 4.3: EWR Configuration Usage Distribution

From this distribution, it appears that only four runway configurations were chosen by the configuration chooser even though there are nine different runway configurations. Why is this the case? Equivalence and dominance preclude some configurations from being chosen when using the maximum operations rate as the operating point criterion.

Consider configurations 1 and 2 at EWR. Configuration 1 uses runway 4R for arrivals and runway 11 for departures; configuration 2 uses runway 4L for arrivals and runway 11 for departures. These two configurations have the same capacity values independent of the flight rule conditions. Because wind is the only factor that eliminates a runway and subsequently a configuration, whenever configuration 1 is deemed active so is configuration 2 and vice versa. Each time the first configuration with the highest capacity is chosen. Therefore, if configurations 1 and 2 have the highest capacity, configuration 1 is always chosen and configuration 2 is never chosen. Because factors other than wind are not considered in configuration choice, our simulation may experience this situation of equivalence.

In practice, there are situations that distinguish configuration 1 and configuration 2. For example, if runway repairs are being made on runway 4R, then configuration 1 is not available and configuration 2 may be the optimal choice. Other factors that are not in this model that affect the choice of runway configuration include noise and previous configuration. Often, airports are under strict noise regulations that prohibit runways from being used. These rules
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encompass both dwell and persistence. Rules dealing with dwell time limit how long a runway can be used continuously while rules dealing with persistence limit how long a runway can be used in a day (not necessarily continuously). Also there are rules which prohibit use of certain runways during specific times of the day. Previous configurations can also affect the choice of configuration. Suppose the best configuration in a time period offered a capacity of 100 operations per hour. Then suppose the conditions changed such that another configuration was available that offered a capacity of 102 operations per hour. An air traffic controller may choose to stay in the configuration with a capacity of 100 because changing configurations may entail shutting down the airport momentarily to change the approaches of incoming flights for the new configuration. The gain of 2 operations per hour may not provide enough benefit to justify the temporary loss of capacity from changing configurations.

Dominance occurs when a configuration is never chosen because it is inferior to another configuration with equal characteristics. For example, consider configurations 3 and 7. Configuration 3 uses both parallel runways. Runway 4R is used for arrivals and runway 4L is used for departures. With configuration 7, only one of the parallel runways is used and it is used for mixed operations. Under VFR conditions the capacity of configuration 3 is 140 operations per hour while the capacity of configuration 7 is 57 operations per hour. Because the direction of the runways are the same for both configurations, whenever configuration 7 can be used, so can configuration 3. Because configuration 3 has the higher capacity, configuration 7 will never be chosen.

All EWR configurations that were not chosen were all equivalent to or dominated by configurations that were.
Figure 4.4 shows the configuration usage distribution using empirical data in the same season as that in Figure 4.3. All of these results were produced using weather data for the months of January and February only unless otherwise noted. Figure 4.4 is based on empirical data from January and February of 1991. However, weather data for that time period was not available; therefore, weather data for the months of January and February from 1986 through 1990 were used to drive the simulation that produced the results illustrated in Figure 4.3. The empirical distribution is similar to those produced by the simulation. Configuration 3 and 4 are the configurations of choice in both cases.

4.1.2. Capacity Coverage

A capacity coverage chart is a summary of the supply of the capacity of an airport. It shows how much capacity is available for what percentage of the time. For example, to validate the results of the EPS values and our simulation process we examined the capacity coverage chart for BOS using weather data from 1990:
This capacity coverage chart indicates that BOS operates in a configuration that provides an airside capacity of 110 operations per hour, 23 percent of the time, an airside capacity of 106 operations per hour another 49 percent of the time, and so on. The capacity of Boston is above 100 operations per hour over 72 percent of the time. This is consistent with facility opinions that there are capacity reductions over 20 percent of the time. This flat portion of the capacity coverage (0 to 72 percent) facilitates more predictable airside performance than an uneven capacity coverage. This aids effective utilization of available facilities because strategic decisions can be made with reference to a stable target level. This is especially important for pacing airports. Capacity coverage charts using EPS values, the FAAACM and the LMIACM all had relatively flat capacity levels.

One must be careful when looking at capacity coverage charts. First of all, there are seasonal effects with capacity levels at an airport.
Figure 4.6 indicates that the capacity reductions are more prevalent in the winter than in the summer. During the winter, BOS operates at an operations rate of greater than 100 operations per hour only 69 percent of the time while during the summer this level of operations can be attained 80 percent of the time.

Another point of consideration is the arrival/departure ratio employed to produce the capacity coverage charts. The capacity coverage charts produced here are based on results using a 50/50 arrival/departure ratio. As shown in Figure 4.7, if one is not careful with arrival/departure ratios, the results may be skewed.
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In Figure 4.7 the capacity levels seem very high about 95 percent of the time. Empirical data shows this to be incorrect. Close examination of the data indicates that for some of the configurations the high capacity levels are due to high departure capacities. For example, one configuration was chosen because it had an arrival capacity of 24 arrivals per hour and a departure capacity of 73 departures per hour. Departures are generally not the bottleneck of an airport and high levels of departure capacity are rarely needed. This should be taken into account when generating capacity coverage charts.

Also, from the capacity coverage charts, we discover that the capacity distributions for airports with multiple sets of parallel runways tend to be multimodal. Consider the following DFW, LAX, and SFO capacity probability distributions:
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Figure 4.8: Capacity Probability Distributions for DFW, LAX, and SFO
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With DFW and LAX, the two modes differentiate the number of parallel runways used. The first mode at DFW representing a capacity of 180 operations per hour occurs when all three pairs of parallel runways are used while the second mode of 145 operations per hour occurs when only two sets are used. Similarly, the first mode in the LAX capacity distribution of 145 operations per hour corresponds to when both pairs of parallel runways are used while the second mode of 90 operations per hour indicates only one pair of parallel runways being used. At SFO, the two sets of parallel runways are perpendicular and the direction of the parallel runways differentiate the two modes. The east-west pair of parallel runways have a capacity of 104 operations per hour and the north-south pair of parallel runways have a capacity of 85 operations per hour.

For airports with only one set of parallel runways or no parallel runways at all, the distribution is unimodal.

![Figure 4.9: Capacity Probability Distributions for BOS and LGA](image)
BOS has one set of parallel runways and has one mode of 102 operations per hour and
LGA has no parallel runways and has a single mode of 72 operations per hour. Also, the
standard deviations of the unimodal distributions are much lower than the multimodal
distributions. The distributions for DFW, LAX and SFO have standard deviations of 35.5,
29.42, and 12.22 respectively. The standard deviations for BOS and LGA are 7.38 and 5.7
respectively. Although there is a greater variance in capacity for airports with multiple runways,
they provide a higher mean capacity.

4.1.3. Capacity Utilization

With EDCFs, capacity utilization charts are created instead of capacity coverage charts.
A capacity utilization chart differs from a capacity coverage chart in that it illustrates the
frequency of capacity utilized rather than the frequency of capacity available. A capacity
utilization chart is used to analyze EDCFs since empirical counts reflect capacity used and not
capacity available. If an airport always operates at capacity then the capacity utilization chart
would be equivalent to the capacity coverage chart. The capacity utilization chart for EWR is
given in Figure 4.10.

![EWR Capacity Utilization Chart](image_url)
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The capacity utilization chart produces a distribution which is slightly sloped as opposed to the level distributions produced by using either the EPS values or the FAAACM. Because different levels and types of demand are experienced at EWR, there are times during the observed peak period when there is a high demand for departures while there are other times during the peak period when there is a high demand for arrivals. Departures take less time than arrivals and thus more departures than arrivals can be inserted in a given length of time. Therefore, during times of high departure demand, the number of operations per hour is greater than during times of high arrival demand. The observed data seems to cover a range of different departure/arrival ratios and thus produce a different shape than the capacity coverage charts. This type of phenomena make it difficult to compare the weather-capacity models to actual capacities realized.

4.1.4. Time Series Results

For capacity time series results, the capacity values output from a simulation run were plotted chronologically.

![Figure 4.11: BOS Time Series Plot](image)

As shown in Figure 4.11, the capacity of BOS is relatively steady at approximately 110 operations/hour. There are a few drops in capacity over the length of the simulation but none of
them are for an extended period of time. By focusing on a one-week period of the plot and magnifying it as in Figure 4.12, the dips in capacity are shown to last for only a few hours.

![BOS 1990 One Week Time Series - FAA](image)

**Figure 4.12: BOS One-Week Time Series Plot**

These dips in capacity may be a result of a couple of different factors. The capacity decreases shown in Figure 4.12 are due to changes in wind conditions. When the capacity of BOS was 110 operations per hour, one of two configurations were being used: configuration 2 which consists of runways 27, 22L, and 22R or configuration 3 which consists of runways 27, 33L and 33R. Unfavorable wind conditions occurred as wind speed increased and wind direction changed. Runway 27 was unaffected but the side runways (22L, 22R, 33L, and 33R) violated maximum crosswind constraints and configurations 2 and 3 became inactive. Before the winds became unfavorable, the crosswind components on the side runways were slightly below 15 knots. When the wind shifted in speed and/or direction the crosswind component was slightly greater than 15 knots. The short spikes seen on either side of the valley are times when the winds shifted such that the crosswind values were hovering around 15 knots. Initially, the crosswind was 14.9 knots, then 15.1 knots then back to 14.9 knots.

In reality, these capacity spikes may not occur. When the wind first changes violating crosswind constraints on the side runways, only runway 27 can be used yielding a capacity of 57
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operations per hour. Even if the crosswind components on the side runways drop below 15 knots, an air traffic controller may choose not to utilize the side runways immediately and wait until the wind has subsided some more.

Another possible reason for capacity decreases are changes in ceiling and visibility. If the ceiling or visibility at an airport changes such that flight rule conditions change, a decrease in capacity can occur.

From the simulation runs, it was found that the changes in flight rule conditions do not occur very regularly and that wind is the most critical weather component. In general, the airports were under VFR1 and occasionally experienced IFR conditions. Wind changes, both in speed and direction, were more frequent. Changes in wind speed and direction can limit an airport to the use of only one runway and can greatly reduce capacity. For instance, BOS prefers to operate with configurations that utilize their parallel runways to achieve high capacity. The changes in the configurations at BOS are a direct result of a change in the wind that either violates the maximum crosswind constraint on a runway making it inactive or changes the direction of the headwind on a runway forcing operations in the opposite direction. A typical day has a relatively steady capacity throughout the day with slight fluctuations due to wind. These fluctuations are greater in airports with multiple sets of parallel runways. When wind forces a runway to become inactive, two runways are affected because the parallel runways are in the same direction.

4.2. Airport Characteristic Analysis

Several conclusions can be made about different airports by specific characteristics in terms of their expected capacity produced by the models studied. The three characteristics that will be discussed here are geographic location in the United States, runways available, and primary use (hub vs. origin/destination)

4.2.1. Geographic Location

The airports examined for this thesis can be classified into three geographic locations: eastern U.S. (BOS, EWR, LGA, and DCA), central U.S. (ATL, DFW, and ORD), and western
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U.S. (LAX and SFO). The wind patterns are different in the different regions. In the eastern U.S., the configurations chosen indicate that winds are from the northwest or the southeast; in the western U.S., the prevailing winds appear to be out of the east or west; meanwhile, no consistent wind pattern exists in the central U.S. This is important because the wind primarily dictates the availability of runways; maximum crosswinds cannot be violated and a headwind is desired. At some airports tailwinds are allowed but at many, they are not.

At BOS the most frequently used runways are runways 4L/22R and 4R/22L. In fact, these runways are used over 90% of the time. Similarly, at EWR the two predominantly used runways are also runways 4L/22R and 4R/22L. These runways were used over 98% of the time in the empirical data. LGA and DCA do not have parallel runways but exhibit similar behavior, as a majority of the configurations used at these airports have runways in the southeast/northwest direction. In the western U.S., LAX and SFO utilize runways that lie east-west with frequency levels similar to runways lying northeast-southwest in the eastern U.S.

Wind patterns throughout the central U.S. may not be consistent but wind at the airports seem to be. For example, DFW primarily uses runways that are north-south while ATL uses runways that lie east-west and correlation in wind patterns is low between those two airports. ATL only has runways that run in the east/west direction. The wind patterns are consistent enough in ATL that this does not pose a problem. Wind rarely blows north-south and when it does, the speed of the wind is low enough that maximum crosswind constraints are not violated.

4.2.2. Runways Available

Parallel runways appear to be the fundamental component to high capacity configurations. Whenever an airport has a set of parallel runways, the most frequently chosen configuration contains a set of parallel runways. BOS and EWR both have one set of parallel runways and these runways are part of the configuration chosen over 85% of the time. ATL, DFW, ORD, LAX, and SFO all have at least two pairs of parallel runways and at least one set, most of the time two sets, is used in the chosen configuration (over 90% of the time).

At DCA and LGA where there are only intersecting runways and no parallel runways, the average capacity is lower than at airports with parallel runways. The average capacity for

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LGA and DCA is about 80 operations per hour while the other airports have an average capacity of 100 operations per hour or higher. Figure 4.13 shows the capacity coverage charts for LAX and LGA to illustrate the capacity differences.

![LAX Capacity Coverage - EPS](image1)

![LGA Capacity Coverage - EPS](image2)

*Figure 4.13: Capacity Coverage Charts for LAX and LGA*

4.2.3. Primary Use of Airport

A hub is an airport that is primarily used for bank operations by a major airline. For example, ORD is a hub airport for United and American Airlines. Aircraft in a flight bank arrive within a short time window; ground crews refuel the aircraft and prepare them for departure; these aircraft compose the flight bank that departs. This process occurs multiple times in a day. The hub airports experience high volumes of traffic and are generally located in the middle of the
country. As it turns out, the airports that were classified in the central U.S. (ATL, DFW, and ORD) are all hub airports.

High capacity is required at a hub airport and to attain this, hub airports utilize multiple sets of parallel runways. ORD and DFW have three pairs of parallel runways while ATL has two pairs. These runways are oriented so that under most wind conditions at least two pairs of parallel runways can be used. As shown below in the capacity coverage chart for DFW, this yields a capacity over 50% greater than the non-hub airports such as BOS or LGA.

DFW has a capacity of at least 145 operations per hour over 90% of the time. From the configuration usage distribution shown in Figure 4.12, it is apparent that this is a result of using mostly one of two configurations. Configuration 3 which is used 50% of the time uses two pairs
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of parallel runways (35L, 35R, 36L and 36R) while configuration 5, used approximately 40% of the time, uses all three pairs of parallel runways.

Ultimately, the information collected using the already existing models, although not optimal, still provides insight into characterizing the capacity of an airport.

4.3. Strengths and Weaknesses of Capacity Models

The simulation process produced varying results for the different capacity models. These results often highlighted the strengths and the weaknesses of the different models. This section describes these strengths and weaknesses.

4.3.1. Empirical Data Capacity Frontiers

The EDCF is different from the other models for several reasons. First, EDCFs are based on historical counts rather than theoretical calculation and thus the capacities given by the EDCF are values that correspond to an operation level that has been achieved before and not a theoretically achievable value.

Also, the model does not necessarily produce maximum throughput capacity levels, although it does give a good estimate of the maximum practical capacity at an airport. In an attempt to get capacity numbers, data was collected at times when the airports were at their peak periods and were thought to be operating at capacity. This does not, however, guarantee that the airport is utilizing all of its capacity. For this reason, the data collected for EDCFs are used to create a capacity utilization chart rather than a capacity coverage chart.

Overall, the EDCF method of capacity estimation has two main weaknesses. First, although data is collected during peak periods of traffic (the definition of which in itself is arbitrary), this method does not necessarily reflect an airport’s actual capacity and can lead to low capacity estimates.

Second, this process is data intensive and it is often difficult to collect sufficient data to produce the frontiers. Consider the situation where EDCFs for an airport with ten configurations is desired. Suppose also that only data points occurring more than once are used to produce the frontiers. Data would need to be collected for forty scenarios (ten configurations with four
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meteorological conditions each) during peak periods and a sufficient number of points for each scenario would be needed taking into account the influence of different arrival/departure profiles.

There is also a tradeoff between quantization accuracy and time spent collecting data as described in chapter 3. Ultimately, if data can be collected for the runway configurations and corresponding flight rule conditions, EDCFs are reasonable estimates of the practical capacity at an airport for given arrival/departure profiles.

4.3.2. Engineered Performance Standards

EPS values have one major appealing characteristic. They are easy to use and acquire. Air traffic flow managers at the pacing airports report their EPS values to the FAA and are requested to do this every three or four years. The FAA compiles this information and therefore, this information can be obtained from one central source.

The strength of the EPS values comes in the process in how they are derived. It is important that facility opinions are solicited and used. This allows for characteristics about the airport not considered in the theoretical capacity calculation to be addressed. This leads to more realistic and accurate values for capacity.

The weakness of the EPS values is that often times for a given configuration and flight rule condition, there is only one capacity value, the one corresponding to a 50/50 mix of arrivals and departures. Occasionally, three capacity values, 25/75, 50/50, and 75/25 arrival/departure ratios, are provided. The small number of data points does not form a very detailed capacity frontier and thus the tradeoff between arrivals and departures is not captured.

The EPS values seem to give fairly accurate results. The configuration usage distributions are nearly identical using EPS values or capacities from the FAAACM. Furthermore, the empirical data suggests a similar distribution. Even when looking at the capacity coverage information produced by the different models, the shape of the distributions are similar. However, close examination of the capacity coverage information, revealed a weakness in the model. EPS values can overestimate departure capacities. Take, for example, the two capacity coverage charts for EWR:
The two distributions have the same shape but the level of capacity varies significantly. The EPS values imply that the capacity of EWR is approximately 140 operations/hour while the FAA values give a capacity value of approximately 80 operations/hour. Using the empirical data for EDCFs (see Figure 4.10) as a basis of comparison of the two models, two conclusions can be made. First, because there are a handful of empirical data points that are at capacity levels close to 140 operations/hour, the capacity level given by the EPS model is attainable. Looking more closely at the data, the high capacity levels are reached when departures compose a majority of the operations. The empirical data indicates that these high capacity levels do not occur often and we infer that most of the time the demand for airfield resources is not dominated by
departures. For this reason, demand composition may be important in choosing a capacity model.

4.3.3. FAA Airfield Capacity Model

Initially, the FAAACM was the most appealing model for accurate capacity frontier generation because of its generality. Most airport configurations are covered by this model. It is a logical model which produces capacity values that correspond to historical data. It also allows the user to specify different arrival and departure ratios so that a frontier can be generated. However, after a detailed investigation the FAAACM was found to have limitations as well. The source of appeal for the FAAACM was that it is a general model that can be used for any airport configuration.

There are two limitations to the FAAACM. First, getting accurate input values is tedious and difficult. Inputs such as runway occupancy times, their standard deviations, and the variance of interarrival times are not recorded by the FAA [26]. These inputs either need to be modeled themselves or empirically measured. For example, there is a model that can be used to estimate the time it takes for an aircraft to clear a runway depending on the average speed of the aircraft, the location of the exits, and the operations on other runways. Taking empirical measurements is time intensive and can be inaccurate. For instance, if measuring the average arrival runway occupancy time, one must determine exactly when an aircraft crosses the threshold and when exactly it has exited the runway.

Second, the FAAACM uses questionable assumptions in capacity calculations for certain configurations. One such assumption is that flight rule conditions do not affect capacity for certain configurations. For example, in the single runway case, the capacity of the configuration is the same regardless of whether the airport is under VFR or IFR conditions. Empirical results have shown this to be false [21]. Under IFR conditions the separations between aircraft tend to be farther apart and thus interarrival times tend to be greater than under VFR conditions. This results in a reduction of capacity under IFR conditions.

Another assumption that seems counterintuitive is that all runways are not used in a capacity calculation. For example, consider again the case of three intersecting runways (one
runway intersecting a pair of parallel runways). To calculate the capacity of the configuration, the model takes the maximum of the capacity of using only the parallel runways or the capacity of using one of the parallel runways with the intersecting runway. There is no benefit in having the third runway. In practice, these capacities are not the same. Our simulation runs were not significantly affected because configurations that were affected were usually not considered by the configuration chooser.

Furthermore, consider Washington National (DCA) where there is a configuration with three intersecting runways. These three runways intersect in a triangular shape. In the FAAACM, three intersecting runways refers to a configuration with one runway intersecting a pair of parallel runways. Under the current FAAACM, DCA’s three runway configuration cannot be easily implemented.

Another characteristic that is not necessarily a limitation of the FAAACM, but simply one to be cautious of, become evident when using the FAAACM with BOS. BOS has a runway (15L/33R) which is a short runway and can only be used by small aircraft. For this reason, configurations that use this runway must be implemented in a slightly different manner. For example, take a configuration which is composed of runways 27, 33L, and 33R. Normally, one would model this as a set of three intersecting runways. Instead, two models must be used. First, the capacity of the configuration of two intersecting runways (27 and 33L) is calculated assuming a fleet mix of only medium, large, and heavy aircraft. Next, 33R is treated as a single runway of mixed operations for small aircraft only. Because of the low percentage of small aircraft at BOS, 33R is utilized infrequently and this configuration is, in essence, a configuration of two intersecting runways.

4.3.4. LMI Airfield Capacity Model

It was difficult to validate the LMI airfield capacity because no empirical data was available for the airports that the LMIACM modeled. Results using the LMIACM for BOS were similar to EPS values and FAAACM values. This provides evidence to conjecture that the LMIACM is an equally accurate model as the others.
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The strength of the model is that there is high fidelity. Very intricate details of operations at the airports are considered and thus produce accurate capacity values, consistent with estimates by local air traffic flow managers and experienced at the airport, for the different configurations under different configurations. This also is a difficulty in the model. The LMIACM is very airport specific and therefore a different model needs to be created for each airport of interest. This expensive tradeoff must be considered when deciding which capacity model is best.

4.4. Recommendations

The solution to an accurate and efficient airfield capacity model is not any one of the models described here. Instead, it is a hybrid of all of the models that incorporates the strengths of all the models while minimizing their weaknesses.

The FAAACM is a good foundation model. It is a general model that takes an analytical approach to calculate the capacity of any configuration. The first recommendation is that this FAAACM be upgraded. All of the different configurations that are used at pacing airports should be modeled. Thus configurations such as DCA's three intersecting runways need to be analyzed and calculated. The calculation logic for the FAAACM is sound but some of the counterintuitive decisions need to be reconsidered.

Although a general model for airfield capacity analysis is important, each airport operates uniquely and these airport specific characteristics should not be overlooked. Therefore, the FAAACM should be used as the "calculate theoretical capacity" part of the EPS calculation process and the second step should be to consult facility opinions. If the theoretical capacity values differ significantly from facility opinions then airport specific issues can be addressed.

After a capacity frontier is generated, airport utilization data should be collected in the same manner as for the EDCFs in order to validate the new model.

The LMIACM does incorporate many of these ideas and may seem to be the solution but its high level of fidelity is not appropriate in many applications. In addition, a significant
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investment in time and money is required to gather the data needed to develop the model at a given airport of interest.
5. Conclusions and Areas for Future Research

With the proposal of new air traffic flow management strategies, it is important to have an environment where these can be tested. This type of environment should be able to give good capacity estimates given the weather conditions at the time. The research in this thesis focused on developing this weather/capacity interaction. With the completion of this research, an environment to test different flow management strategies using airport weather data and a choice of various capacity models can easily be constructed.

5.1. Sawtooth Wave Model

The first part of this research focused on incorporating the SWM as the weather generation portion of the weather/capacity interaction. The SWM is used to generate accurate synthetic weather observations to drive a choice of capacity models. The SWM is a statistical weather model based on historical weather data and appropriate for use in a simulation environment. With this model, the observations generated preserve the spatial correlation among sites, the temporal auto-correlation inherent in weather, and the cross-variable correlation between weather variables such as cloud ceiling and visibility.

One must, however, use discretion when using the SWM. The SWM should be used for a local region. Using one SWM to generate weather for Boston, Texas, California, and Alaska is not advised. When the region is not localized, the homogeneity of spatial and temporal correlation is lost and the SWM loses accuracy. If one is trying to generate weather across the United States, the “breathing earth” model or multiple SWMs should be used.

Further research would enhance the appeal of the SWM. This includes determining the effects of two new weather variables: precipitation and temperature. Precipitation has definite effects on the capacity of an airport and many questions must still be answered before precipitation can be implemented into the SWM. Currently, the effects of precipitation are implicitly incorporated in determining the flight rule conditions. It is reasonable to assume that if precipitation is present and adversely affecting an airport’s operations, then the ceiling and/or
visibility will be low, putting the airport in IFR conditions. This is not always true and thus modeling precipitation would be worthwhile. Along those lines, temperature is also important. Temperature does not have a direct effect on the operation of an airport but often determines the type of precipitation present. It is important to know whether the temperature is below freezing when there is precipitation because rain, snow and ice all have different effects on airport operations.

Future research can also be conducted in the area of forecasting. Although it is possible to model forecasting behavior by using the SWM, a separate forecasting model should be implemented to eliminate any bias that using the SWM might introduce. Forecasting is important because air traffic flow managers plan at the beginning of a day based on forecasted capacities. These may be different from realized capacities and can affect the results of different flow management strategies.

Ultimately, the simplicity and flexibility of the SWM make it appealing for use in air traffic control flow management research but there is still more that can be done to enhance it.

5.2. Capacity Models

The second area of research for this thesis was to compare four different capacity models and determine if any one was more suitable than the others for implementation. Because the SWM as well as each of the four capacity models are stand alone models, implementing any of the capacity models to be driven by the outputs of the SWM was not difficult.

The research showed that all models had some definite strengths and weaknesses. Overall, the major tradeoff present among the models was between the fidelity of the results and the difficulty of generating the input data requirements. A hybrid of the different capacity models which attempts to incorporate each one’s strength was proposed and is an area for future research. Other areas of future research looking at different models used to derive input parameters. For example, for the FAAACM several inputs are difficult to collect empirically such as runway occupancy times or variances of interarrival times. Models to derive these type
of statistics have been or are currently being developed and their inclusion into the capacity models should be considered.

Overall, the SWM provides good input weather data and each of the different models produces reasonable capacity estimates. We still recommend implementation of a new capacity model such as the hybrid suggested to balance the tradeoff between input data required and fidelity of results produced. Nevertheless, the current capacity models provide useful insight about capacities at pacing airports.
Chapter 5: Conclusions and Areas for Future Research
Appendix A: Sample Input Files

A.1: Sample Input File for Weather Generation

0014 total number of waves chosen
0003 total sites chosen
BOS 42.22 -71.00 city (3 chars) latitude longitude
DCA 38.51 -77.02 city (3 chars) latitude longitude
LGA 40.47 -73.52 city (3 chars) latitude longitude
1008.0 hours
0005 number of dimensions for ceiling/visibility
160.06 reference separation distance for cv
0.76 reference correlation for ceiling/visibility
18.08 Tau for ceiling/visibility
0.63 ceiling to visibility correlation
0004 number of dimensions for x-wind
160.06 reference separation distance for x-wind
0.71 reference correlation for x-wind
13.25 Tau for X-wind
0004 number of dimensions for y-wind
160.06 reference separation distance for y-wind
0.74 reference correlation for y-wind
16.9 Tau for Y-wind
Appendix A: Sample Input Files

A.2: Sample Input File for Simulation

```
EWR  //city code
Newark  //city or airport name
-13  //magnetic deviation (degrees)
800  //ceiling (feet) limit for IFR2
1000 //ceiling (feet) limit for IFR1
2500 //ceiling (feet) limit for VFR2
1  //visibility (miles) limit for IFR2
3  //visibility (miles) limit for IFR1
5  //visibility (miles) limit for VFR2
10  //number of EPS ids

1  //EPS id
1  //number of points for frontier
04R   //arrival runway configuration
11   //departure runway configuration
62  65 //IFR2 arrival, departure, point 1
67  67 //IFR1 arrival, departure, point 1
67  67 //VFR2 arrival, departure, point 1
67  73 //VFR1 arrival, departure, point 1

2  //EPS id
1  //number of points for frontier
04L   //arrival runway configuration
11   //departure runway configuration
62  65 //IFR2 arrival, departure, point 1
67  67 //IFR1 arrival, departure, point 1
67  67 //VFR2 arrival, departure, point 1
67  73 //VFR1 arrival, departure, point 1

3  //EPS id
1  //number of points for frontier
04R   //arrival runway configuration
04L   //departure runway configuration
62  65 //IFR2 arrival, departure, point 1
67  67 //IFR1 arrival, departure, point 1
67  67 //VFR2 arrival, departure, point 1
67  73 //VFR1 arrival, departure, point 1

4  //EPS id
1  //number of points for frontier
22L   //arrival runway configuration
22R   //departure runway configuration
62  65 //IFR2 arrival, departure, point 1
67  67 //IFR1 arrival, departure, point 1
67  67 //VFR2 arrival, departure, point 1
67  73 //VFR1 arrival, departure, point 1

5  //EPS id
1  //number of points for frontier
29   //arrival runway configuration
```
Appendix A: Sample Input Files

22L //departure runway configuration
62 65 //IFR2 arrival, departure, point 1
67 67 //IFR1 arrival, departure, point 1
67 67 //VFR2 arrival, departure, point 1
67 73 //VFR1 arrival, departure, point 1

6 //EPS id
1 //number of points for frontier
29 //arrival runway configuration
22R //departure runway configuration
62 65 //IFR2 arrival, departure, point 1
67 67 //IFR1 arrival, departure, point 1
67 67 //VFR2 arrival, departure, point 1
67 73 //VFR1 arrival, departure, point 1

7 //EPS id
3 //number of points for frontier
04R //arrival runway configuration
04R //departure runway configuration
12 40 //IFR2 arrival, departure, point 1
22 22 //IFR2 arrival, departure, point 2
26 8 //IFR2 arrival, departure, point 3
12 40 //IFR1 arrival, departure, point 1
22 22 //IFR1 arrival, departure, point 2
26 8 //IFR1 arrival, departure, point 3
14 43 //VFR2 arrival, departure, point 1
24 24 //VFR2 arrival, departure, point 2
28 9 //VFR2 arrival, departure, point 3
14 43 //VFR1 arrival, departure, point 1
24 24 //VFR1 arrival, departure, point 2
28 9 //VFR1 arrival, departure, point 3

8 //EPS id
3 //number of points for frontier
22L //arrival runway configuration
22L //departure runway configuration
12 40 //IFR2 arrival, departure, point 1
22 22 //IFR2 arrival, departure, point 2
26 8 //IFR2 arrival, departure, point 3
12 40 //IFR1 arrival, departure, point 1
22 22 //IFR1 arrival, departure, point 2
26 8 //IFR1 arrival, departure, point 3
14 43 //VFR2 arrival, departure, point 1
24 24 //VFR2 arrival, departure, point 2
28 9 //VFR2 arrival, departure, point 3
14 43 //VFR1 arrival, departure, point 1
24 24 //VFR1 arrival, departure, point 2
28 9 //VFR1 arrival, departure, point 3

9 //EPS id
3 //number of points for frontier
29 //arrival runway configuration
29 //departure runway configuration
0 0 //IFR2 arrival, departure, point 1
Appendix A: Sample Input Files

0 0  //IFR2 arrival, departure, point 2
0 0  //IFR2 arrival, departure, point 3
12 40 //IFR1 arrival, departure, point 1
22 22 //IFR1 arrival, departure, point 2
26 8  //IFR1 arrival, departure, point 3
14 43 //VFR2 arrival, departure, point 1
24 24 //VFR2 arrival, departure, point 2
28 9  //VFR2 arrival, departure, point 3
10   //EPS id
3    //number of points for frontier
11   //arrival runway configuration
11   //departure runway configuration
12 40 //IFR1 arrival, departure, point 1
22 22 //IFR1 arrival, departure, point 2
26 8  //IFR1 arrival, departure, point 3
12 40 //IFR1 arrival, departure, point 1
22 22 //IFR1 arrival, departure, point 2
26 8  //IFR1 arrival, departure, point 3
14 43 //VFR1 arrival, departure, point 1
24 24 //VFR1 arrival, departure, point 2
28 9  //VFR1 arrival, departure, point 3
14 43 //VFR1 arrival, departure, point 1
24 24 //VFR1 arrival, departure, point 2
28 9  //VFR1 arrival, departure, point 3
## Appendix B: Table of Configurations

<table>
<thead>
<tr>
<th>Airport</th>
<th>Configuration Number</th>
<th>Arrival Runways</th>
<th>Departure Runways</th>
<th>Configuration Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATL</td>
<td>1</td>
<td>8L, 9R</td>
<td>8R, 9L</td>
<td>Four Parallel</td>
</tr>
<tr>
<td>ATL</td>
<td>2</td>
<td>26R, 27L</td>
<td>26L, 27R</td>
<td>Four Parallel</td>
</tr>
<tr>
<td>ATL</td>
<td>3</td>
<td>8R, 9R</td>
<td>8R, 9L</td>
<td>Three Parallel</td>
</tr>
<tr>
<td>ATL</td>
<td>4</td>
<td>26L, 27L</td>
<td>26L, 27R</td>
<td>Three Parallel</td>
</tr>
<tr>
<td>ATL</td>
<td>5</td>
<td>8L, 9R</td>
<td>9L</td>
<td>Three Parallel</td>
</tr>
<tr>
<td>ATL</td>
<td>6</td>
<td>9R</td>
<td>8, 9L</td>
<td>Three Parallel</td>
</tr>
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## Appendix B: Table of Configurations

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## Appendix B: Table of Configurations

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Technical Interviews:

21. Bourgoin, B.L., Boston Air Traffic Control Tower, Logan International Airport, MA.


23. Gilbo, E.P., Volpe National Transportation Systems Center, MA.

24. Odoni, A. R., Massachusetts Institute of Technology, MA.

25. Lee, D. A., Logistics, Management Institute, VA