Prediction of International Flight Operations at Sixty-six U.S. Airports

by

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Abstract

This report presents a top-down methodology to forecast annual international flight operations at sixty-six U.S. airports, whose combined operations accounted for 99.8% of the total international passenger flight operations in National Airspace System (NAS) in 2004. The forecast of international flight operations at each airport is derived from the combination of passenger flight operations at the airport to ten World Regions. The regions include: Europe, Asia, Africa, South America, Mexico, Canada, Caribbean and Central America, Middle East, Oceania and U.S. International.

In the forecast, a “top-down” methodology is applied in three steps. In the fist step, individual linear regression models are developed to forecast the total annual international passenger enplanements from the U.S. to each of nine World Regions. The resulting regression models are statistically valid and have parameters that are credible in terms of signs and magnitude. In the second step, the forecasted passenger enplanements are distributed among international airports in the U.S. using individual airport market share factors. The airport market share analysis conducted in this step concludes that the airline business is the critical factor explaining the changes associated with airport market share. In the third and final step, the international passenger enplanements at each airport are converted to flight operations required for transporting the passengers. In this process, average load factor and average seats per aircraft are used.

The model has been integrated into the Transportation Systems Analysis Model (TSAM), a comprehensive intercity transportation planning tool. Through a simple graphic user interface implemented in the TSAM model, the user can test different future scenarios by defining a series of scaling factors for GDP, load factor and average seats per aircraft. The default values for the latter two variables are predefined in the model using 2004 historical data derived from Department of Transportation T100 international segment data.

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I am also grateful to my family, to whom I am truly indebted. It is the continued support and love from my grandfather, parents, and brother that makes me believe that life is not only white and black, it is more colorful. The work is also dedicated to my grandmother who died ten years ago for the memory of her generous love to everyone in her life.

Eventually, thanks God for his great mercy and countless blessing. I knew clearly that is why I have been surrounded by the angelic people wherever I went and have received much more than what I deserved.

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Chapter 1 Introduction

1.1 Background and Motivation

International passenger demand is a very important component of the air transportation system in the United States. According to Federal Aviation Administration (FAA) statistics, international passenger enplanements in the United States grew by 17.6 million between the years 2002 and 2005. A robust increase of 5% in the international passenger demand is also expected between 2006 and 2017 [1].

Historical trends show that a high proportion of international passenger traffic is concentrated at large international airports in the U.S. between 1990 and 2000 (see Figure 1), and the total number of U.S. international passenger enplanements grew from 44.2 to 72.9 million. This represents an annual average growth rate of 5.1%. During the same period, the proportion of international enplanements relative to total enplanements increased from 9.1% to 10.6%.

Figure 2 shows the international enplanements share relative to the total enplanements at top 20 airports between 1990 and 2004. It should be noted that at the Miami International Airport, the international enplanements share is above 45% in 2004. In the past 15 years, the international airline passenger enplanements share experienced a noticeable growth at the top 20 airports as shown in Figure 2.

Combined with the forecast of domestic flight operations, the forecasted international flight operations can be used for policy making, airport planning, marketing, and investment decision making. For example, total (domestic plus international) flight operations can be used in the capacity-delay analysis of an airport. Since aircraft size of international flights are generally larger than that of domestic flights, the impact of an international flight on the airport operation is relatively larger than that of a domestic flight.

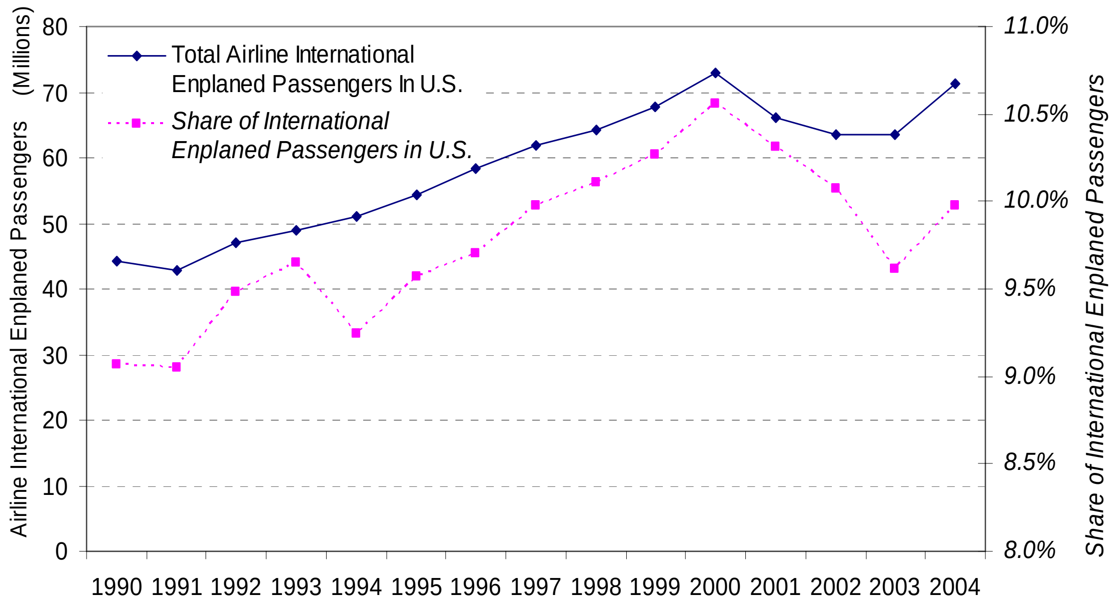


Figure 1. Historical Trend of Enplaned International Passengers and Proportion of them over Total Enplaned Passengers in the U.S.

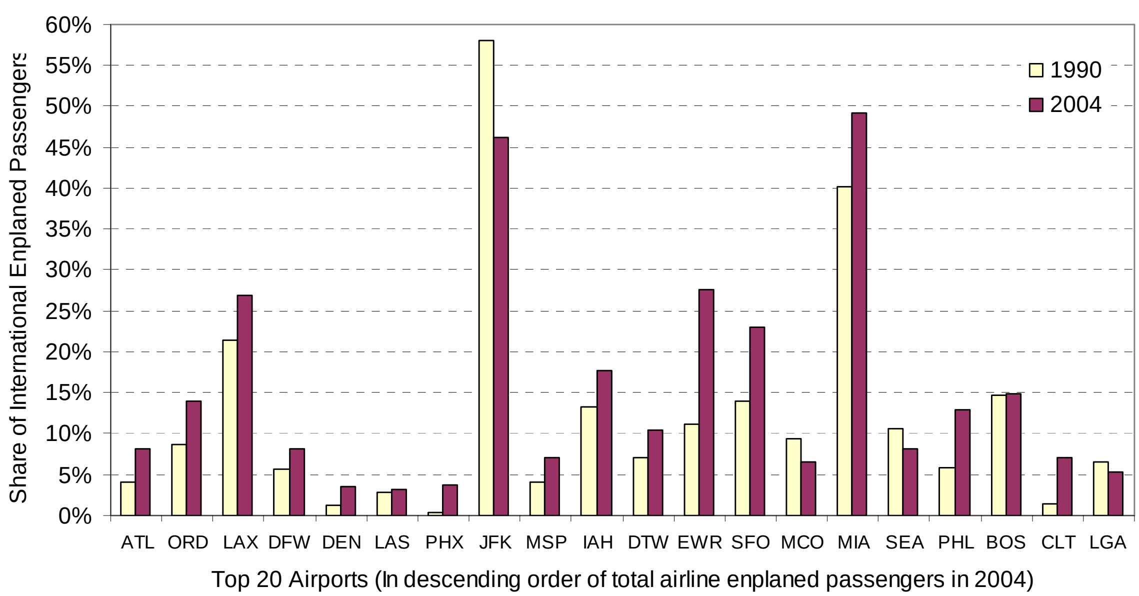


Figure 2. Share of International Passengers over Total Passengers at Top 20 U.S. Airports.

Considering the greater impact of international flights on airport operations and the fast growth of international air travel along with its proportion relative to the total air traffic at airports in U.S., it is essential to include international operations in any type of airport analysis such as capacity-delay analysis, and future airport expansion plans. Unfortunately, few publicly-available methods exist to forecast international air travel demand.

1.2 Scope of Work

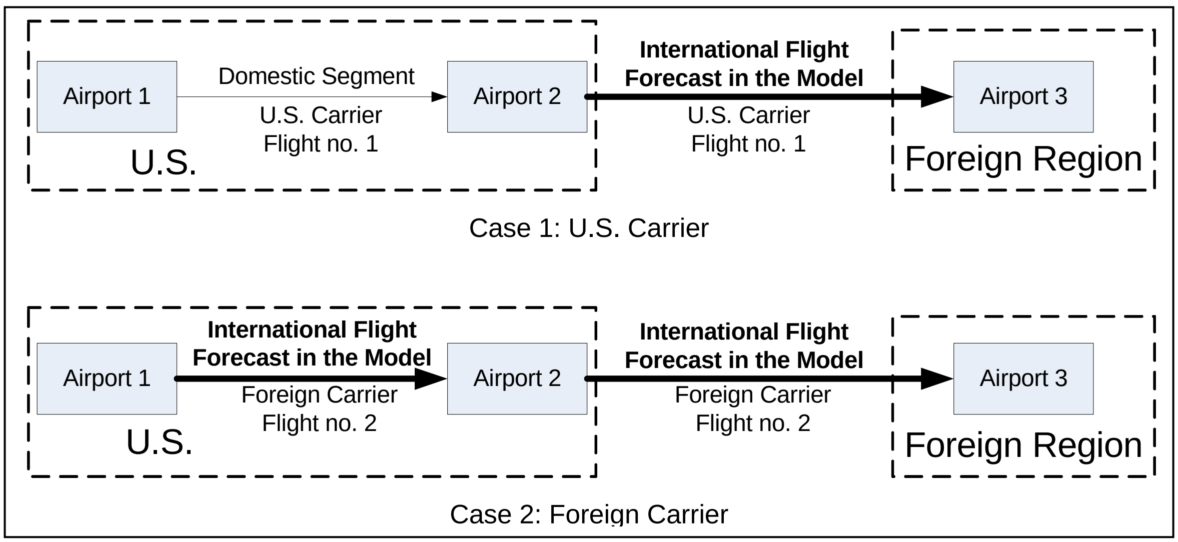


Figure 3. Defined International Passenger Flight Operations in the Analysis.

In this study, international passenger enplanements are defined as the number of people who depart from U.S. airports on any nonstop commercial international flight operated by U.S. or foreign carriers. The international airline passenger operations considered are any nonstop passenger flights operated by the U.S. carriers to and from a U.S. airport, or any passenger flights operated by foreign carriers to and from a U.S. airport. For example, a flight flown from U.S. airport 1 to foreign airport 3 via U.S. airport 2 as shown in Figure 3; if it is operated by a U.S. carrier as illustrated in Case 1, only the second segment of this flight is forecast in this analysis because the first segment is a domestic flight. On the other hand, both segments of the flight are classified as international flights if the flight is operated by a foreign carrier (Case 2). For example, a flight operated by Korean Airlines from IAD (Washington D.C., U.S.) to ICN (Seoul, Korea) stops over at John Kennedy International Airport (JFK, New York, U.S.) to carry passengers from JFK to ICN. In this case we estimate two departure operations for only one flight: one at IAD and another one at JFK. The first one is an international flight within the U.S. It is grouped as a "U.S. to U.S. international operation". The other nine foreign groups are labeled as "U.S. to Europe", "U.S. to Asia", etc.

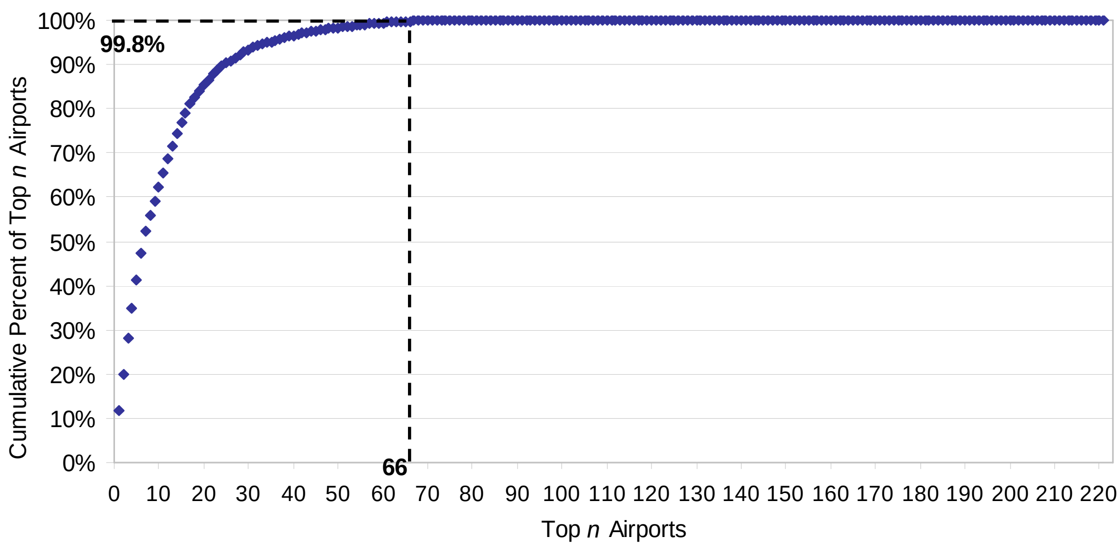


Figure 4. Cumulative Percent of Total International Passenger Flight Operations in the U.S. in Year 2004.

In this analysis, the forecast of international passenger flight operations focuses on 66 U.S. international airports. In 2004, the combined operations at these 66 airports accounted for 99.8% of total international passenger flight operations in the United States. In 2004, 443 airports in the continental U.S. had commercial operations, and 223 of these airports served international passenger flights. The best source of information to study international operations at U.S. airports is the international T-100 segment data offered by the U.S. Department of Transportation (DOT). For each of the 223 international airports, T-100 International Segment data includes information about the foreign destination airport, World Area Code (WAC) of the destination country, passengers and available seats for all the non-stop flights (A sample of T-100 data is enclosed in

Appendix A). Figure 4 shows all the international airports ranked according to their international operations in 2004. The figure shows that the top 20 airports account for 85.3% of the total U.S. international operations. The top 66 airports account for 99.8% and many of the 223 international airports have too few international flight services to be considered regular services. For example, some airports had only 2 operations in one year. Therefore, the analysis focuses on the top 66 airports with reliable international air passengers. International flight operations at the top 66 airports in 2004 are listed in Table 1.

The forecasting horizon (or time frame of a forecast) is the number of periods in the future covered by the forecast. The accuracy of a forecast depends partly on the time frame associated with the forecast. Therefore, the forecasting time frame is very important factor to consider when select the right forecasting method. In this analysis, the forecast horizon is 26 years starting in the year 2005 and ending in 2030.

In addition, it should be noted that the forecasts presented in this analysis are "unconstrained" in nature. Any existing physical or policy constraints at U.S. international airports will not be taken into consideration in the forecasting process. Since the international service is the main source of profit for many of the legacy airlines, it is reasonable to assume that the international air travel demand at each airport will not be constrained in the short term even though the total number of operations at some airports may be limited by the airport capacity.

Table 1. International Passenger Flight Operations at top 66 U.S. Airports in Year 2004.

Rank	Airport	International Passenger Flight Operations	Share of Total International Passenger Flight Operations in the U.S.	Cumulative Percent
1	MIA	136,802	11.7%	11.7%
2	JFK	98,086	8.4%	20.0%
3	LAX	95,602	8.1%	28.2%
4	ORD	80,892	6.9%	35.0%
5	IAH	74,260	6.3%	41.4%
6	EWR	70,342	6.0%	47.4%
7	ATL	57,016	4.9%	52.2%
8	DFW	43,562	3.7%	55.9%
9	SFO	38,602	3.3%	59.2%
10	FLL	37,774	3.2%	62.4%
11	BOS	36,572	3.1%	65.6%
12	PHL	36,246	3.1%	68.7%
13	SEA	34,860	3.0%	71.6%
14	IAD	33,200	2.8%	74.4%
15	DTW	30,154	2.6%	77.0%
16	MSP	25,060	2.1%	79.2%
17	LGA	22,440	1.9%	81.1%
18	CLT	17,838	1.5%	82.6%
19	PHX	17,298	1.5%	84.1%
20	DEN	15,026	1.3%	85.3%
21	MCO	14,394	1.2%	86.6%
22	CVG	14,336	1.2%	87.8%
23	LAS	11,588	1.0%	88.8%
24	DCA	8,814	0.8%	89.5%
25	PIT	8,166	0.7%	90.2%
26	CLE	7,744	0.7%	90.9%
27	PBI	7,642	0.7%	91.5%
28	BWI	7,366	0.6%	92.2%
29	PDX	7,314	0.6%	92.8%
30	LKE	6,002	0.5%	93.3%
31	SLC	5,670	0.5%	93.8%
32	BDL	4,948	0.4%	94.2%
33	MKE	4,078	0.3%	94.5%
34	SFB	3,796	0.3%	94.9%
35	ALB	3,734	0.3%	95.2%
36	SAT	3,706	0.3%	95.5%
37	MEM	3,312	0.3%	95.8%
38	RDU	3,142	0.3%	96.1%
39	TPA	2,924	0.2%	96.3%
40	STL	2,812	0.2%	96.5%
41	OAK	2,704	0.2%	96.8%
42	CMH	2,496	0.2%	97.0%
43	HPN	2,306	0.2%	97.2%
44	MDW	2,260	0.2%	97.4%
45	SJC	2,182	0.2%	97.6%
46	IND	2,002	0.2%	97.7%
47	MHT	1,948	0.2%	97.9%
48	SAN	1,892	0.2%	98.1%
49	MDT	1,720	0.1%	98.2%
50	PVD	1,684	0.1%	98.3%
51	ABE	1,662	0.1%	98.5%
52	ONT	1,468	0.1%	98.6%
53	TUS	1,384	0.1%	98.7%
54	BFI	1,370	0.1%	98.8%
55	MSY	1,354	0.1%	99.0%
56	ROC	1,258	0.1%	99.1%
57	BNA	1,100	0.1%	99.2%
58	MCI	1,044	0.1%	99.3%
59	RSW	1,018	0.1%	99.3%
60	PIE	1,014	0.1%	99.4%
61	DAB	926	0.1%	99.5%
62	MLB	904	0.1%	99.6%
63	ELP	638	0.1%	99.6%
64	SMF	598	0.1%	99.7%
65	MFE	484	0.0%	99.7%
66	MYR	370	0.0%	99.8%
Total 1 (the top 66 U.S. international airports)		**1,170,906**	**99.8%**	-
Total 2 (all the U.S. international airports)		**1,173,704**	**100.0%**	-

1.3 Objective and Approach

The purpose of this analysis is to forecast annual international flight operations at the top sixty-six international U.S. airports over the period 2005 to 2030. To perform such forecast, a "top-down" methodology is applied in three steps. In the fist step, individual linear regression models are developed to forecast the total annual international passenger enplanements from the U.S. to each of nine World Regions. The resulting regression models are statistically valid and have parameters that are credible in terms of signs and magnitude. In the second step, the forecasted passenger enplanements are distributed among international airports in the U.S. using individual airport market share factors. The airport market share analysis conducted in this step concludes that the airline business is the critical factor explaining the changes associated with airport market share. In the third and final step, the international passenger enplanements at each airport are converted to flight operations required for transporting the passengers. In this process, average load factor and average seats per aircraft are used.

1.4 Organization of the Document

The remaining of this document is organized as follows: Chapter 2 is devoted to review previous studies pertinent to general forecasting techniques. Forecasting techniques are classified into several categories based on the quantitative and qualitative characteristic of the techniques. In Chapter 3, details of the methodology used in forecasting international operations at 66 U.S. airports are presented. In this chapter, we investigate the historical trend and general relationship between variables. Various types of preliminary analyses are conducted. Chapter 4 focuses on evaluating the performance of the models developed in Chapter 3. The forecasted passengers from U.S. to World Regions and international passenger flight operations at airports are also examined. In Chapter 5, we present a summary of results of this study and suggest directions for future research.

Chapter 2 Literature Review

2.1 Categorization of General Forecasting Techniques

From the methodological viewpoint, forecasting techniques can be classified into three groups: quantitative, qualitative and decision analysis (See Figure 5). Quantitative methods predict future numeric data mainly using historical trends. Quantitative forecasting techniques rely on the availability of historical data. These methodologies cannot be applicable if the relevant data cannot be collected. In this situation, Qualitative methodologies might be applied based on some experts' or key people's judgment, intuition and experience. The third methodology is the combination of the first two.

The forecasting methods can be applied at either macro-level or micro-level. The macro-level forecasting model focuses on the forecast of more collective variables, while the micro-level forecast focuses on more detailed and disaggregated variables. For example, the macro-level forecast projects total annual international passengers or total flight operations from the U.S. to Asia in future years, whereas the micro-level forecast focuses on hourly flights at a specific airport in the future. Based on the time span for which forecasting models project, the models can be also classified as either short-term (usually less than ten years forecasting period) or long-term (up to several decades) models.

In the next section, general characteristics of qualitative and quantitative forecasting methods along with some practical applications in air travel demand are presented.

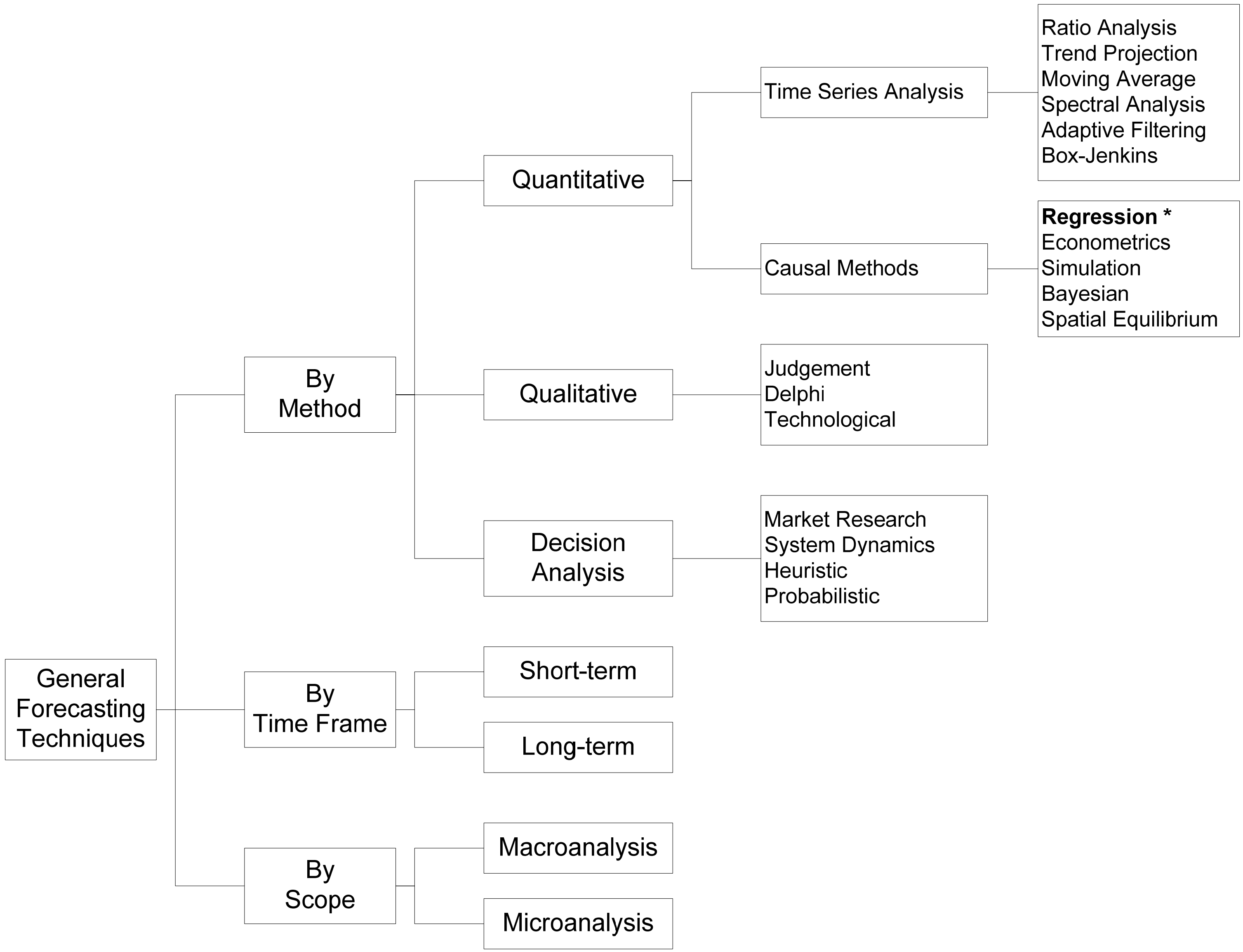


Figure 5. General Forecasting Techniques and Categories.

2.1.1 Qualitative Forecasting Techniques

Qualitative forecasting methods are used more appropriately when historical data concerning the events to be predicted are either scarce or unavailable, or when the events to be forecasted are affected by non-quantifiable information or by technology changes.

Judgment, Delphi and technological forecasting are qualitative methods typically applied in research. The benefit of the qualitative method is that both quantifiable and unquantifiable information can be used in the forecasting process. However, it is impossible for the qualitative method to measure or improve the forecast accuracy because no systematic model is used. Besides, the forecasts may contain built-in biases of the experts given the subjectivity involved with the qualitative methods. In practice, qualitative techniques are used less frequently in the forecasting process than quantitative methods discussed in the following section.

2.1.2 Quantitative Forecasting Techniques

In contrast to qualitative methods, quantitative forecasting methods analyze historical data (or historical trend) statistically to identify a pattern, and then apply a mathematical model to emulate the pattern. The estimated equation of the model is used to forecast the trend into the future. This quantitative approach relies on the assumption that the identified pattern will continue into the future. Quantitative models are further grouped into two types: time-series analysis and causal methods. Both time-series and causal methods have gained widespread acceptance because they offer several advantages. First, the forecasts are objectively conducted once the explanatory variable(s) and the functional form of the model are determined. Second, the accuracy and statistical validity of the resulting model can be tested using statistical methods. Additionally, various types of computer packages are readily available for the modelers to apply quantitative methods efficiently. A range of forecast values based on confidence intervals can be developed using quantitative methods.

A. Time Series Analysis

Time-series analysis forecasts the future value of dependent variable applying statistical analysis only to historical (or time series) data of the variable. Time-series analysis assumes that one may forecast the value of a variable by studying only the historical pattern of that variable over time. Time-series analysis is known to be very effective in predicting short-term forecasts such as monthly, weekly, daily or hourly variations in demand. The simple exponential smoothing technique is the most commonly used in time series analysis dealing with fluctuating patterns. However, significant developments have also been made in techniques such as moving average, adaptive filtering, Box-Jenkins methods, and spectral analysis.

Numerous air transportation forecasts using time series analysis can be found in the literature. For example, the method of smoothing the data using running medians is used by Meyn to calculate the revenue passenger-kilometers flown by Indian Airlines from April, 1976 to December, 1980 [3]. The advantage of this approach is that the computations are easy to follow and consequently to modify.

Various Box-Jenkins Autoregressive Integrated Moving (ARIMA) models are adopted to estimate the tourist arrivals to Australia from Hong Kong, Malaysia and Singapore by Lim and McAleer [4]. The forecast interval of this model is a quarter period and the model covers all quarters from 1975-1989. The best fitting ARIMA model is chosen first by using the mean absolute percentage error and the root mean squared error (RMSE) as measure of forecast accuracy. The forecasts are then obtained after the best fitting ARIMA is found. The Box-Jenkins approach is very flexible and useful but also somewhat complicated in developing forecasting models especially when a large number of historical time-series data needs to be analyzed.

B. Causal Models

Causal models assume that the dependent variable to be forecasted can be explained by the behavior of another or set of independent variables. The purpose of the causal model is to discover the form of the relationship (mathematical curve) between all the variables by statistical analysis, and to use it to forecast future values of the dependent variable. Time-series models that focus on when an event will happen, while causal models concentrate on why an event happened. The most commonly used causal model is the regression-based model.

The advantage of using a regression model is that it is relatively easy to conduct the forecast when the projected explanatory variables are available. If the independent variable is rather difficult to observe, the regression model is useless to forecast regardless of how good the calibrated model fits the historical data.

Sen developed a city-pair model using stepwise multiple linear regression analysis to forecast the air travel demand between 40 city pairs involving 20 cities in India between 1986 and 2001 [5]. In this model, the socioeconomic characteristics of the two city pairs and supply characteristics of the transport system are used as explanatory variables. Among the supply characteristics used are: the travel time ratio between rail and air; a dummy variable to indicate big-city proximity factor that is related with frequency of service; the number of nonstop or minimum-stop flights and the type of aircraft. The statistical and logical validity of the model is evaluated by two different approaches: cross-validation and a backward prediction. The model is reported to have R^2 of 95.2%.

Karlaftis developed several simple linear regression models to forecast the air passenger demand at Miami International Airport and Frankfurt International Airport [6]. GDP and Gross National Product (GNP) are used as explanatory variables to forecast the international and domestic air travel respectively.

A San Diego airport study by Simat Helliesen & Eichner, Inc. (SH&E) [7] forecasts international passenger demand through 2030 under the assumption that there is no capacity constraint. The study uses future growth rates available in FAA and Boeing forecasting models [1] & [13] and predicts international air travel demand between the United States and six World Regions: Asia-Pacific, Atlantic, Mexico & Canada, Latin America, Central America and South America.

In another study, a logarithmic model between Origin and Destination (O&D) passenger by U.S. State and Gross State Product (GSP) is estimated by Bhadra and Wells [8]. The resulting model explains the variations in O&D passenger travel by state accurately.

An intercity gravity model is developed by Fridstrom and Thune-Larsen to forecast the air traffic volumes on the entire air transportation Norwegian network [9]. Income, population, travel times and fares are taken into account as explanatory variables for estimating intercity air travel demand elasticity based on combined cross-section and time-series data.

2.2 International Air Travel Demand Forecasting

The advantages of econometric models in forecasting long-term trends make them very attractive and they have been adopted in modeling the air travel demand by Federal Aviation Administration (FAA) and large aircraft manufacturers such as Boeing and Airbus. These organizations have published their forecasts of international aviation operations. In the publications, the air travel demand is usually modeled as a linear function of traditional macroeconomic variables such as GDP and trade [10].

The *Terminal Area Forecast* (TAF) [11] is a detailed FAA forecast planning database produced by the Office of Aviation Policy, Planning and Environment (APO). The forecast covers all the airports that included in the National Plan of Integrated Airport System (NPIAS). It is updated every year and the most updated TAF database (February 2006) spans from 2005 to the year 2025. The TAF predicts air traffic demand at airports using a top-down framework. First, the national-level passenger enplanements are forecasted using macroeconomic variables such as income, population and energy price combined with some time-series model. In a second step, the estimated national passenger enplanements are allocated to specific airports considering the historical shares of the airport, master plans and expert opinion [12].

The FAA also provides forecasts of annual international passengers demand between the United States and the rest of the world over a 12-years forecast period. Every year, the FAA publishes the "*FAA Aerospace Forecast*" [1], which contains both historical and forecasts of future international aviation demand for mainline commercial air carriers, commuter airlines and general aviation. The international aviation demand includes total international passengers to and from the United States to four world areas: Atlantic, Pacific, Latin American and Canada. This forecast is an international air travel demand at the national level. No the airport specific international demand is included in the analysis. Passengers, Revenue Passenger Kilometers (RPK) and Available Seat Kilometers (ASK) for each area of the world are predicted. Future load factors and average seats per aircraft of the international flights are also included in the report. The projection of world economic data such as GDP and exchange rates of U.S. and various world areas are considered in the analysis. The historical international passenger data used in the report is collected from United States Immigration and Naturalization Services (INS) and Transport Canada. The economic data is obtained from Global Insight.

Unfortunately, the functional form of the forecasting model used in the "FAA Aerospace Forecast" is not publicly available. However, it can be inferred from the data tables included in the report that the international passenger demand prediction is based on an econometric model using historical passenger statistics and both historical and projected world economic data.

In contrast to FAA, aircraft manufacturers such as Boeing and Airbus focus passenger traffic prediction of RPK and fleet mix rather than passengers and operations. Every year, Boeing and Airbus publish individual assessments of the world air travel demand, but neither of their forecast models is published. As aircraft manufacturers, their emphasis is to predict future aircraft fleet mixes required to satisfy domestic and international air travel demand. The "*Current Market Outlook*" [13] and the "*Global Market Forecast*" [14] represent the views of Boeing and Airbus to predict annual air travel demand over a span of 20 years. Boeing updates their forecast every year, while the latest Airbus Global Market Outlook was released in December 2004. Boeing and Airbus forecasts share a common vision of a strong air travel demand growth over the whole forecast horizon. In the "*World Global Market*", Airbus models the air passenger demand based on different sets of economic and air transport variables. The projections of economic growth and other indices are obtained from the Global Insight Forecasting Group. World passenger traffic is forecasted to increase 5.3% annually and the number of flight operations expected to double over the period 2004-2023. Boeing considers Gross Domestic Product as the major contributor to the growth in air travel demand. Other determinants of air travel growth are lower fares, additional world trade, and increase in frequencies and more direct service. In the *Current Market Outlook* (2004), passenger traffic is expected to grow by 5.2% per year, and World GDP is forecasted to grow by 3.0% annually over the next 20 years. In terms of the forecast of fleet mix, Airbus and Boeing hold opposite views. Airbus predicts that:

> "*Unlike passenger airlines under pressure to improve service levels by increasing frequencies, freight operators generally have little incentive to increase frequencies beyond once-daily service and are more likely to respond to growing traffic by increasing aircraft size and thereby achieving lower unit operating costs*".

Boeing on the other hand says that "*Airlines will provide passengers point-to-point service on busy routes*" and "*Airlines will maintain or reduce airplane size to provide frequent, nonstop service*".

The diverging views of Boeing and Airbus had major consequences in the development of their future aircraft. Boeing is developing the 787 to offer airlines with a family of efficient aircraft to serve more frequent point-to-point markets. Airbus, on the other hand developed the Airbus A380 to achieve lower unit operating cost with an increased aircraft size.

2.3 Lessons from the Literature Review

It was found that many of the air travel demand forecast models use economic variables such as GDP, population, air fare and trade etc as explanatory variables to explain the dependent variables such as total number of passengers, flight operations, and revenue per mile [12]. The commonly used functional form of the model is a linear model [6].

As pointed out, the functional form of the forecasting model for international travel demand is not available in the FAA, Boeing, and Airbus projections although they publish their forecast results every year. Their forecasts of international air travel demand are projected at the national level. In our review, very few papers were found to forecast the international flight operations at the airport level.

Learning from the previous studies, it is reasonable to use regression models to forecast international air travel demand using economic variables such as GDP, Trade and others. It should be noted that, practically, it is extremely difficult and time consuming to collect socio-economic data for each airport. This implies that it is more appropriate to apply a “top-down” approach that starts from a prediction of total international travel demand at national level and then split the total demand to various airports.

A simple regression model is also recommended as a modeling technique to forecast the passenger enplanements from the U.S. to each World Region [6]. Most studies conclude that world GDP along with average fares and trade are the key factors determining international air travel demand. The resulting econometric models indicate that world GDP and other measures of income will positively affect international air travel between U.S. and the rest of the world. Ian increase in the average fare negatively affects the air travel demand.

Chapter 3 Methodology and Data Collection

The forecast of passenger flight operations at an airport is derived from the passenger flight operations at the airport to each of ten defined World Regions. The regions include: Europe, Asia, Africa, South America, Mexico, Canada, Caribbean and Central America, Middle East, Oceania and U.S. International. A top-down approach is adopted in the forecasting process. It starts with aggregate-level forecasts of international passenger enplanements from the U.S. to each World Region. The airport's market share of international passenger enplanements by World Region is investigated further to split the nationwide international passenger enplanements to individually airports. Projections of average seats per aircraft and average load factor are applied to convert the international passenger enplanements to passenger flight operations at each airport. The procedures to execute this top-down approach are shown in Figure 6. In the figure, red, green and blue are used to indicate historical data, identify forecast level and highlight the benefits of our approach, respectively. Bold black letters show the output of each step. The following paragraphs describe the process.

Step 1: Forecast the international passenger enplanements from the U.S. to each World Region over the forecast period between 2005 and 2030. An individual regression model is developed for each World Region using this procedure. The historical international passenger enplanements from the U.S. to each World Region and historical GDP of each World Region between 1990 to 2004 years are inputs to the regression model.

Step 2: Allocate the forecast international passenger enplanements by World Region to each airport under study based on the assumed airport market share for future years. Historical airport shares are investigated and considered as the basis for projecting future airport market shares.

Step 3: Convert the international passenger enplanements projected at each airport by World Region to passenger flight operations using projected average aircraft size and load factors. An analysis of historical trends of average aircraft size and load factor is required in this step.

Each step described above will be discussed in detail in the following sections.

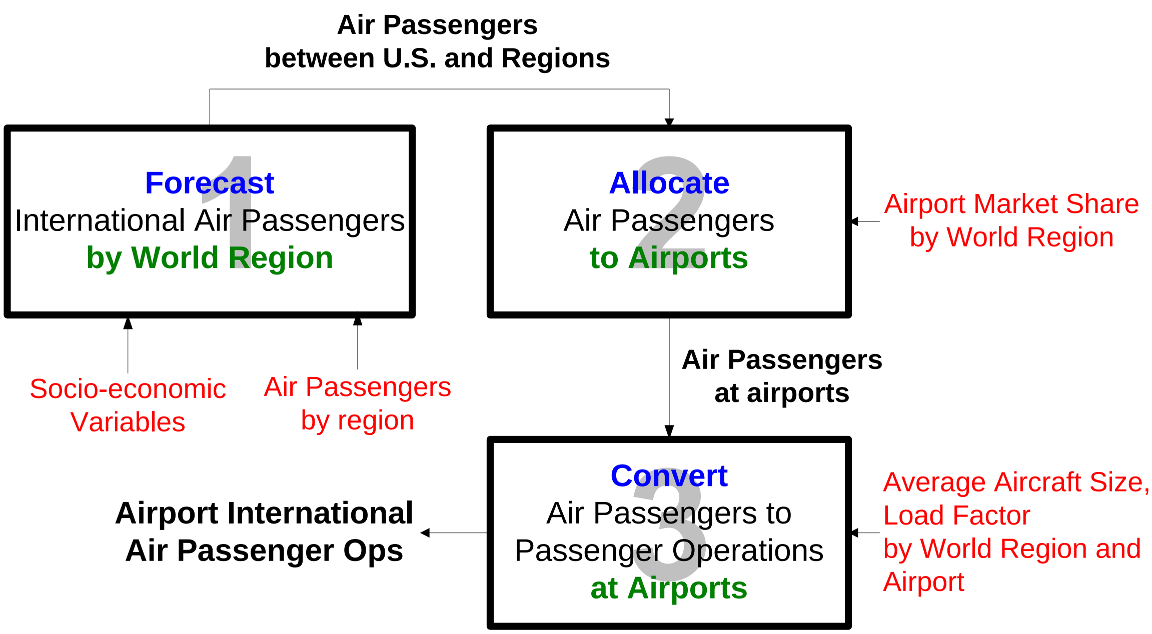


Figure 6. Overview of Top-down Methodology Used to Predict International Passenger Demand.

For practical reasons, the number of international flight operations is assumed to be twice the number of projected international departures at each U.S. airport since the commercial operations between almost all the origin-destination pairs are round trips. In other words, it is assumed that the number of departures and arrivals at each airport are the same.

The model developed assumes that the total annual international flight operations at each U.S. airport are unconstrained by airport capacity. In other words, it is assumed that additional airspace and airport capacity would be available to accommodate the growth in passenger enplanements in the future. An effort was made to identify how and when airport capacity restricts international air travel demand at each airport. The analysis was not conclusive because many of the airports experienced drastic changes in international flight operations caused by airline bankruptcies rather than airport capacity-delay problems.

3.1 Forecast International Passenger Enplanements by World Region

The first step of the "top-down" approach to derive the international passenger flight operations at airports is to forecast the international passenger enplanements from the U.S. to each World Region. The approach is based on econometric and statistical analyses that rely on time-series data obtained from publicly available sources. Individual simple linear regression models are developed to forecast the international passenger enplanements from the U.S. to each World Region. Figure 7 shows the steps used in the regression analysis.

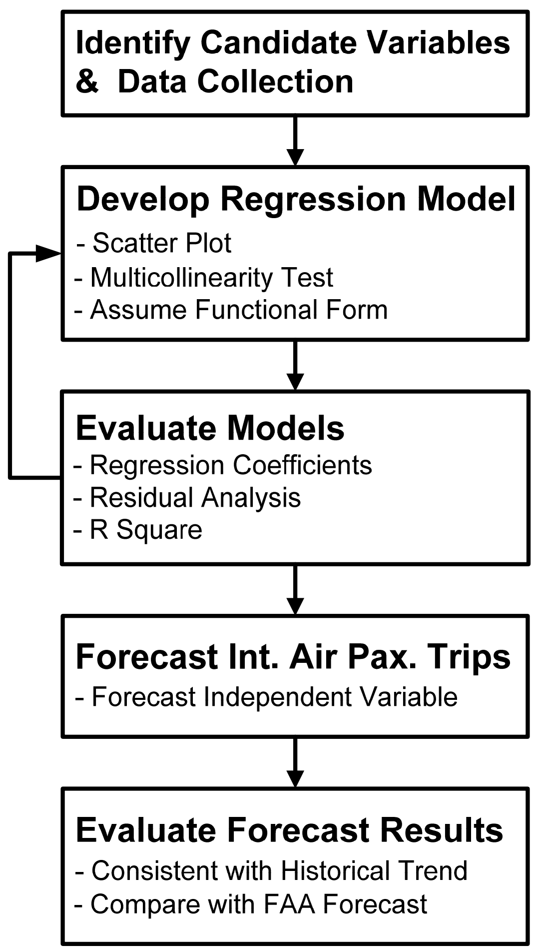


Figure 7. Regression Model Framework Used to Predict International Air Transportation Demand.

The forecast of the international passenger enplanements from the U.S. to each World Region begins with the identification of candidate explanatory variables along with the data collection of both historical dependent and explanatory variables. In each regression model, GDP of origin (the U.S.) and destination (each World Region) are both considered as the candidate explanatory variables. Knowing that the events of Sep. 11, 2001 caused a permanent reduction in international air travel demand, a dummy variable is introduced in the model to account for this effect. The statistical validity and accuracy of the estimated model is evaluated using standard statistical tests. These are described in Chapter 4. The forecast of international passenger enplanements from the U.S. to each World Region is forecast by applying the selected model. Each one of the steps above is explained in detail in the following sections.

3.1.1 Data Collection

A. Dependent Variable

The historical data of passenger enplanements from the U.S. to each World Region over the period of 1990 to 2004 is extracted from T-100 international segment data [2]. The data includes all traffic arriving to and from U.S. airports on non-stop commercial international flights and passengers operated by either U.S. or foreign carriers. T-100 International Segment data is publicly available at the U.S. DOT, Bureau of Transportation Statistics website. A sample screen capture of data is presented in Appendix A. The T100 segment data has certain limitations. Prior to October 1, 2002, air carriers that operated aircraft with 60 seats or less were not included in T100 International Segment data. Therefore prior to October 1, 2002, the passenger volumes to Canada, Caribbean and Central America regions are underrepresented because passengers served by small aircraft are not reported. It should be noted that some anomalies were also found in the T-100 International Segment data. In some instances, the annual average seating capacity of some aircraft was found to be less than the passengers they served. In other instances, the seating capacity of aircraft is misrepresented. For example, the seating capacity of Boeing 747-200 is found to be 600 in several T100 international segment data records, but the Boeing 747-200 aircraft can only hold 420 seats maximum due to safety regulatory standards. It is also observed that the international air passenger data summarized from T-100 International Segment data does not exactly match the statistics published by FAA for the same category. In spite of these abnormalities, T-100 is still the most valuable and comprehensive data to understand international enplanements and flight operations. For all the reasons explained before, we use the T-100 International Segment data as the basic source of international enplanements and flight operations data in our analysis. The detailed process for modification of T-100 International Segment data is presented in Figure 8.

The historical international passenger enplanements from U.S. to each World Region are summarized in Table 2.

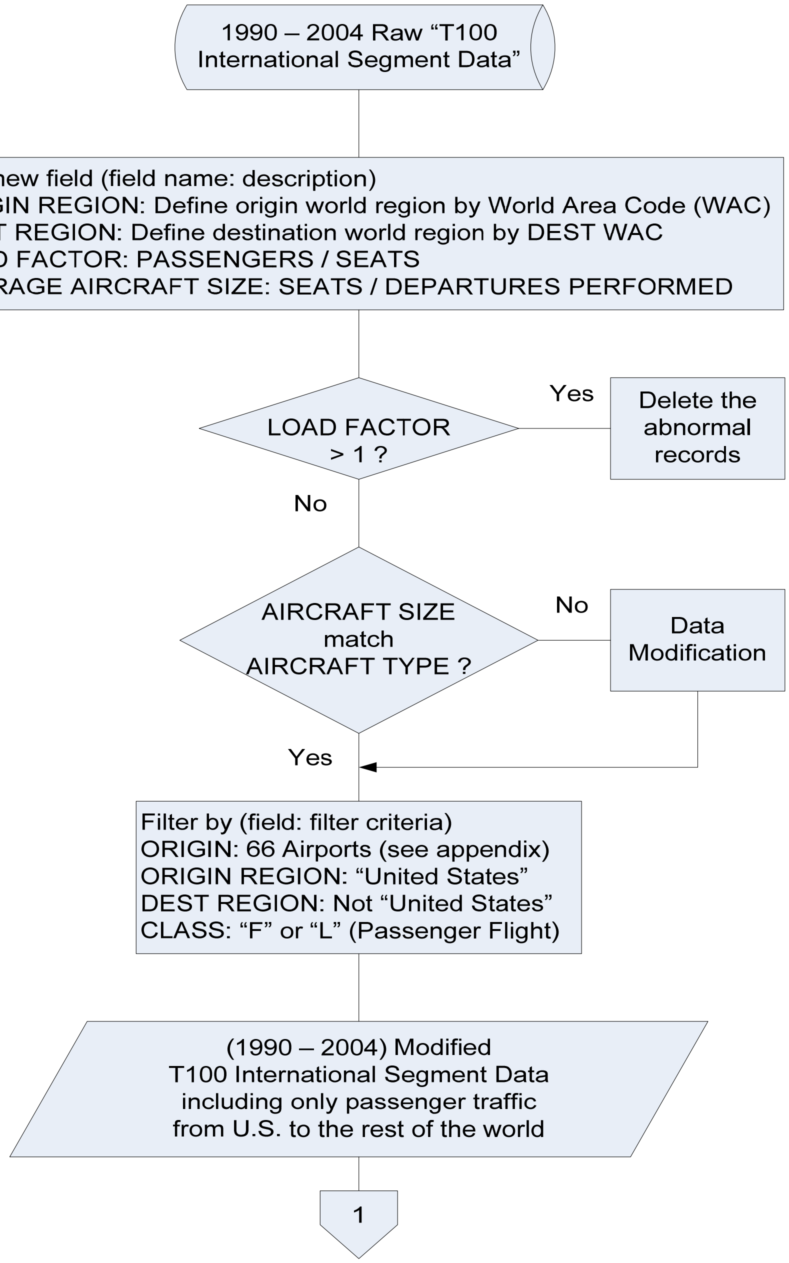


Figure 8. Flowchart for Evaluation and Modification on T100 International Segment Data.

Table 2. 1990 - 2004 Historical Airline International Non-stop Passengers from U.S. to each World Region.

Year	Europe	Africa	Middle East	Canada	Asia	Oceania	South America	Caribbean & Central America	Mexico	Total
1990	14,236,619	93,256	272,998	6,686,221	6,921,660	1,180,032	1,873,048	6,000,332	4,918,602	42,182,768
1991	13,032,798	87,741	289,015	6,104,449	6,850,355	1,164,494	2,064,972	6,084,958	5,140,737	40,819,519
1992	14,984,234	125,765	337,487	6,454,628	7,638,951	1,207,249	2,387,481	6,181,456	5,482,372	44,799,623
1993	15,707,676	142,991	374,925	6,513,949	7,861,951	1,227,403	2,719,399	6,893,246	5,494,245	46,935,785
1994	16,368,294	173,721	440,728	6,415,064	8,765,578	1,223,365	3,049,244	6,914,268	5,696,279	49,046,541
1995	17,182,886	225,249	550,093	6,982,548	9,921,310	1,279,100	3,525,938	7,349,025	5,567,783	52,583,932
1996	18,536,009	255,957	601,123	7,690,269	10,749,955	1,351,267	3,618,815	7,359,170	6,345,073	56,507,638
1997	20,140,153	299,493	608,421	8,072,931	11,215,034	1,336,430	4,038,897	7,562,965	6,890,303	60,164,627
1998	21,877,589	296,902	659,661	8,439,888	10,271,658	1,335,846	4,272,178	8,244,687	7,168,019	62,566,428
1999	23,627,497	339,747	732,607	8,649,282	10,669,654	1,458,207	4,198,584	9,070,424	7,694,034	66,440,036
2000	25,732,084	366,258	792,226	9,076,426	11,559,810	1,663,001	4,301,053	9,670,774	8,370,185	71,531,817
2001	22,905,223	354,276	615,962	8,537,700	10,269,315	1,502,264	3,944,233	9,354,333	7,655,390	65,138,696
2002	21,471,529	281,963	551,341	8,480,826	10,064,819	1,435,610	3,509,822	9,428,369	7,379,806	62,604,085
2003	21,526,594	305,867	607,101	8,526,212	8,773,002	1,502,685	3,490,096	10,298,876	7,810,406	62,840,839
2004	23,750,001	304,931	803,779	9,629,240	10,587,193	1,623,315	3,838,378	10,894,814	9,046,488	70,478,139

Source: United States Department of Transportation (DOT), Bureau of Transportation Statistics (BTS), T-100 International Segment Data, http://www.transtats.bts.gov/.

B. Explanatory Variables

Historical information on GDP for each World Region in the period of 1990 to 2004 is obtained from data provided by the Economic Research Service (ERS) [15]. ERS is the primary source of economic information for the U.S. Department of Agriculture. The international Macroeconomic Data Set including gross domestic product (GDP), population, real exchange rates and other variables are publicly available since 1969.

The projection of GDP for the period of 2005 until 2016 is collected from ERS. The GDP of each World Region from 2017 to 2030 is forecast by applying average growth rates obtained from the GDP forecasts from 2005 to 2016. Since ERS only supplies a projection of World GDP until 2016, the World GDP from 2017 to 2030 is forecast by applying the average growth rate obtained from the GDP forecast from 2005 to 2016.

The historical and projected GDP values used in the model development are presented in Tables 3 and 4, respectively.

Table 3. 1990 - 2004 Historical World Regions' GDP (in millions of 2000 U.S. Dollars).

Year	Europe	Africa	Middle East	Canada	Asia	Oceania	South America	Caribbean & Central Camerica	Mexico	U.S.
1990	7,153,748	403,788	696,732	527,581	5,823,897	336,554	918,939	130,525	407,320	7,120,470
1991	7,198,864	408,008	747,157	517,505	6,065,221	337,547	964,812	134,391	424,518	7,085,089
1992	7,263,981	408,844	781,780	522,222	6,252,234	348,653	1,003,334	139,527	439,922	7,302,181
1993	7,246,885	410,832	816,110	534,241	6,427,609	364,439	1,049,860	144,612	448,503	7,497,324
1994	7,454,082	421,543	824,062	559,502	6,658,366	381,230	1,104,360	148,811	468,306	7,802,978
1995	7,645,279	436,273	856,841	582,288	6,916,341	398,408	1,143,653	154,637	446,519	7,972,800
1996	7,787,351	460,182	900,908	591,663	7,254,969	413,200	1,180,964	160,203	469,486	8,271,400
1997	7,993,273	475,531	936,107	616,778	7,498,263	429,231	1,241,305	166,709	501,212	8,647,600
1998	8,227,861	492,153	961,561	641,948	7,472,977	448,296	1,257,612	173,779	525,805	9,012,500
1999	8,456,659	507,885	964,364	677,961	7,658,158	465,968	1,239,032	181,488	545,464	9,417,100
2000	9,007,076	524,711	1,022,950	713,796	8,001,389	475,996	1,273,261	188,402	581,326	9,817,000
2001	9,163,374	542,893	1,029,385	727,379	8,154,130	493,799	1,275,863	192,365	580,629	9,890,700
2002	9,266,365	560,810	1,062,682	751,127	8,291,441	509,838	1,251,140	196,686	584,855	10,048,800
2003	9,357,604	583,802	1,119,221	766,149	8,645,185	531,286	1,270,121	201,944	592,474	10,320,600
2004	9,574,453	612,217	1,191,373	788,368	9,045,797	549,564	1,357,937	208,126	618,543	10,755,700

Source: United States Department of Agriculture, Economic Research Service, http://www.ers.usda.gov/Data/Macroeconomics/.

Table 4. 2005 - 2030 Forecast World GDP (in millions of 2000 U.S. Dollars).

Year	Europe	Africa	Middle East	Canada	Asia	Oceania	South America	Caribbean & Central Camerica	Mexico	U.S.
2005*	9,715,317	642,509	1,254,259	812,807	9,381,683	562,634	1,419,992	215,035	642,048	11,153,661
2006*	9,903,614	674,081	1,315,724	837,191	9,724,505	580,215	1,474,108	221,849	666,445	11,544,039
2007*	10,143,626	707,186	1,376,706	862,307	10,078,300	598,996	1,529,781	227,273	691,770	11,924,992
2008*	10,380,550	740,329	1,437,582	888,176	10,447,065	619,015	1,587,243	233,599	718,058	12,294,667
2009*	10,611,550	773,281	1,499,974	914,822	10,831,848	639,878	1,647,013	241,568	745,344	12,675,802
2010*	10,846,179	806,637	1,564,690	942,266	11,232,718	661,437	1,708,984	250,185	773,667	13,068,752
2011*	11,082,188	840,950	1,632,001	970,534	11,650,629	683,717	1,772,514	259,063	803,066	13,460,814
2012*	11,314,768	876,459	1,702,029	999,650	12,089,438	706,740	1,838,483	268,200	833,583	13,864,639
2013*	11,552,128	913,071	1,774,890	1,029,640	12,550,003	730,532	1,906,659	277,591	865,259	14,280,578
2014*	11,789,509	951,056	1,850,520	1,060,529	13,033,989	755,117	1,976,886	287,217	898,139	14,708,995
2015*	12,028,489	990,192	1,929,113	1,092,345	13,542,910	780,522	2,049,395	297,099	932,268	15,135,556
2016*	12,272,686	1,031,009	2,011,103	1,125,115	14,078,735	806,783	2,124,594	307,391	967,694	15,574,487
2017*	12,521,841	1,073,509	2,096,578	1,158,869	14,635,760	833,928	2,202,554	318,039	1,004,467	16,026,147
2018*	12,776,054	1,117,760	2,185,685	1,193,635	15,214,823	861,985	2,283,373	329,057	1,042,636	16,490,905
2019*	13,035,427	1,163,835	2,278,580	1,229,444	15,816,797	890,987	2,367,159	340,456	1,082,257	16,969,142
2020*	13,300,067	1,211,810	2,375,423	1,266,327	16,442,588	920,965	2,454,019	352,250	1,123,382	17,461,247
2021*	13,570,079	1,261,762	2,476,381	1,304,317	17,093,138	951,951	2,544,066	364,452	1,166,071	17,967,623
2022*	13,845,572	1,313,773	2,581,631	1,343,446	17,769,428	983,980	2,637,417	377,078	1,210,381	18,488,684
2023*	14,126,659	1,367,928	2,691,354	1,383,750	18,472,474	1,017,086	2,734,193	390,140	1,256,376	19,024,856
2024*	14,413,452	1,424,315	2,805,740	1,425,262	19,203,337	1,051,307	2,834,521	403,656	1,304,118	19,576,577
2025*	14,706,067	1,483,027	2,924,988	1,468,020	19,963,116	1,086,678	2,938,530	417,639	1,353,675	20,144,297
2026*	15,004,623	1,544,159	3,049,304	1,512,061	20,752,956	1,123,240	3,046,356	432,107	1,405,114	20,728,482
2027*	15,309,240	1,607,811	3,178,904	1,557,423	21,574,046	1,161,032	3,158,138	447,076	1,458,509	21,329,608
2028*	15,620,042	1,674,087	3,314,012	1,604,145	22,427,623	1,200,096	3,274,021	462,563	1,513,932	21,948,167
2029*	15,937,153	1,743,094	3,454,862	1,652,270	23,314,971	1,240,473	3,394,157	478,587	1,571,461	22,584,663
2030*	16,260,702	1,814,947	3,601,699	1,701,838	24,237,427	1,282,210	3,518,702	495,166	1,631,177	23,239,619
Average Annual Growth:										
1990-2004	**2.1%**	**3.0%**	**3.9%**	**2.9%**	**3.2%**	**3.6%**	**2.8%**	**3.4%**	**3.0%**	**3.0%**
2004-2010	**2.1%**	**4.7%**	**4.6%**	**3.0%**	**3.7%**	**3.1%**	**3.9%**	**3.1%**	**3.8%**	**3.3%**
2010-2016	**2.1%**	**4.2%**	**4.3%**	**3.0%**	**3.8%**	**3.4%**	**3.7%**	**3.5%**	**3.8%**	**3.0%**
2016-2030	**2.0%**	**4.1%**	**4.3%**	**3.0%**	**4.0%**	**3.4%**	**3.7%**	**3.5%**	**3.8%**	**2.9%**
2004-2030	**2.1%**	**4.3%**	**4.3%**	**3.0%**	**3.9%**	**3.3%**	**3.7%**	**3.4%**	**3.8%**	**3.0%**

Source: 2005 - 2016: United States Department of Agriculture, Economic Research Service, http://www.ers.usda.gov/Data/Macroeconomics/.

2017 - 2030: Virginia Tech, Air Transportation System Lab, https://secure.hosting.vt.edu/www.atsl.cee.vt.edu/index.htm.

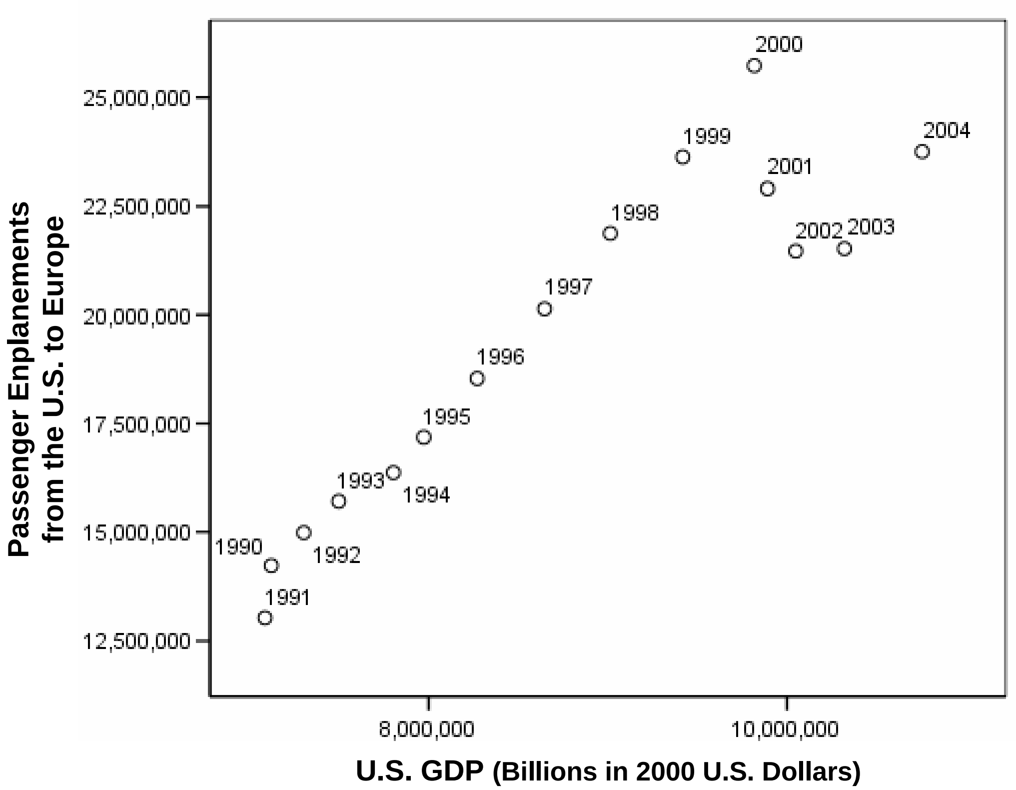
3.1.2 Model Development

Once the candidate variables of the model have been determined and the data has been collected and verified, the model is ready to be calibrated using statistical techniques and multiple regression analysis. The statistical software SPSS 14.0 is used in the analysis.

A. Scatterplot and Correlation Matrix

Before running the regression analysis, a series of scatter plots of each independent variable against the dependent variable are examined to identify their relationship [16]. The graphical analysis is helpful to identify the relationship between two variables. Additionally, the graphical analysis provides certain clues about the need for data transformation. Such information is not easily found when looking the data in tabular form. If the regression analysis is performed without graphical analysis, some significant relationships between the transformed data may be missed.

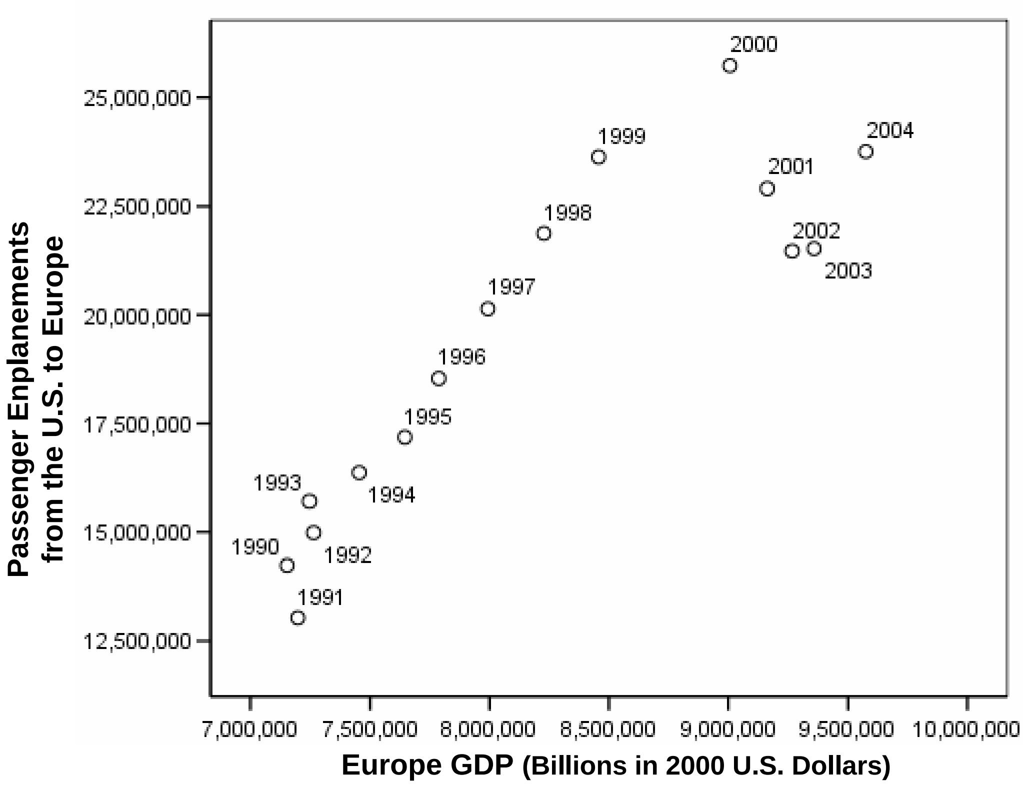
Apparent linear relationships are observed between both origin (the United States) and destination (each World Region) GDP and the historical international passenger enplanements from the U.S. to each World Region. Therefore, both GDPs can be presented in linear regression equation directly, no data transformation is required. As the candidate explanatory variables, GDP of both origin and destination are tested against the number of passenger enplanements from U.S. to each World Region. As shown in Figures 9 and 10, the air passenger enplanements from the U.S. to Europe increases with increasing European GDP and U.S. GDP between 1990 and 2000. A substantial decrease of international passenger enplanements from U.S. to Europe in 2001 is noted in spite of increasing GDP. As explained later in this chapter, the behavior is attributed to the events of Sep. 11, 2001 and so a dummy variable is needed to explain this unusual impact.



Source: Enplanements: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

GDP: United States Department of Agriculture, Economic Research Service, http://www.ers.usda.gov/Data/Macroeconomics/.

Figure 9. Scatterplot of Passenger Enplanements from the U.S. to Europe vs. U.S. Real GDP (2000 U.S. Dollars).



Source: Enplanements: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

GDP: United States Department of Agriculture, Economic Research Service, http://www.ers.usda.gov/Data/Macroeconomics/.

Figure 10. Scatterplot of Passenger Enplanements from the U.S. to Europe vs. Europe Real GDP (2000 U.S. Dollars).

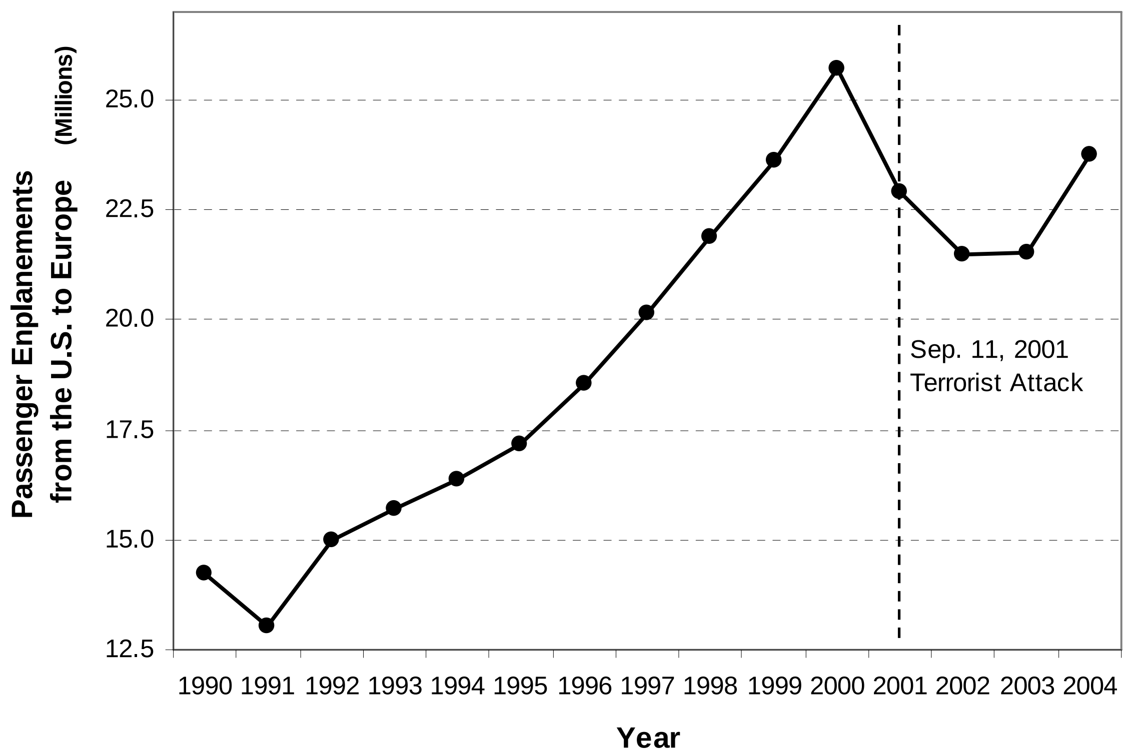
The second step is to obtain a correlation matrix between explanatory variables. Running correlations among the independent variables is helpful to prevent multicollinearity problems (multicollinearity will be addressed in the *model evaluation* section later in this chapter). The bivariate correlations procedure in SPSS is used in this analysis to compute Peason's correlation coefficient between all the independent variables. The correlation coefficient measures how variables are linearly related. It ranges in value from -1 (a perfect negative relationship) and +1 (a perfect positive relationship). A value of 0 indicates no linear relationship. Table 5 presents the correlation coefficients results between U.S. GDP and each World Region's GDP. Since high linear correlations between U.S. GDP and World Regions' GDP are observed, they cannot be included in the regression model at the same time. For this reason, we only use the World Region's GDP in each one of the regression models developed.

Table 5. Pearson Correlation Coefficients between U.S. GDP and World Region's GDP.

		Africa _GDP	Asia_ GDP	Europe _GDP	Canada _GDP	Caribbean _CA_GDP	Mexico _GDP	Middle East_GDP	Oceania _GDP	SAmerica _GDP
US_ GDP	Pearson Correlation	.988**	.987**	.991**	.995**	.998**	.990**	.983**	.996**	.930**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	15	15	15	15	15	15	15	15	15

**. Correlation is significant at the 0.01 level (2-tailed).

Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/

Figure 11. Trend of Historical Air Passengers from the U.S. to Europe.

A dummy variable is also introduced to account for the international air passenger reduction caused by the Sep. 11, 2001 terrorist attack. Over the historical period between

1990 and 2004, the growth of international passenger enplanements has been steady except for two periods as shown in Figure 11. The first reduction in international air transportation demand is linked with the first Gulf war. The second reduction in demand reflects the impacts of Sep. 11, 2001. Based on the assumption that the events of the Sep. 11, 2001 terrorist attack caused a permanent reduction in international air passenger trip demand, a dummy variable is defined as 1.0 throughout the forecast period since the year 2001, otherwise, it is zero.

B. Assumed Functional Form of the Model

It has been already found that a strong linear relationship exists between both origin (U.S.) and destination (World Region) GDP and the international passenger enplanements from the U.S. to each World Region. Taken multicollinearity effects into consideration, the U.S. GDP is excluded from the regression models developed. Additionally, a dummy variable is found necessary to account for the effects of Sep. 11, 2001 terrorist attack on the international air travel demand. The following functional relationship is assumed for forecasts of international passenger enplanements from the U.S to each World Region:

$$\mathrm{APT}_{\mathrm{U.S.\_i\_t}} = \beta_0 + \beta_1 \mathrm{GDP}_{\mathrm{i\_t}} + \beta_2 \mathrm{D}_{\mathrm{911\_t}} + e_t, e_t \sim N(0, \sigma^2) \quad (1)$$

where:

$\mathrm{APT}_{\mathrm{U.S.\_i\_t}}$ = Total international passenger enplanements from the U.S. to World Region *i* in year *t*

$\mathrm{GDP}_{\mathrm{i\_t}}$ = Total real general domestic production ($ 2000 U.S. dollars) of World Region *i* in year *t*

$\mathrm{D}_{\mathrm{911\_t}}$ = Dummy variable to account for Sep. 11, 2001 terrorist attack in year *t* (for t < 2001, $\mathrm{D}_{\mathrm{911\_t}}$ = 0, otherwise $\mathrm{D}_{\mathrm{911\_t}}$ = 1)

e_t = The error term in year *t* that cannot be explained by GDP and the dummy variable

$\beta_0, \beta_1, \beta_2$ = Parameters to be estimated through calibration

In the study, the coefficients of the explanatory variables are determined by linear regression analysis using the SPSS software program [16].

3.1.3 Model Evaluation

After the model is calibrated, it is of critical importance to perform some statistical tests to support the assumptions made during the regression analysis. All the regression coefficients also need to be examined statistically for significance. Additionally, the forecasting accuracy of the model should be evaluated. All the related tests are introduced in the following sections.

A. Tests of Assumptions Underlying Regression Analysis

As the first step in analyzing the regression output, the residual analysis is conducted to test the assumptions underlying in the regression models. The classic ordinary least square procedure for estimating the regression coefficients for each independent variable assumes the following [6]:

- The forecast errors are normally distributed with a mean of zero.
- The forecast errors are statistically independent of each other (no autocorrelation).
- The variance of the forecast error is constant across all observations and values of independent variables (homoscedasticity).

The regression analysis assumes that the forecast errors or residuals are normally distributed with a mean of zero. The forecast residual e_i is defined as the difference between Y_i (the actual value of dependent variable) and $\hat{Y}$ (the value predicted by the estimated regression equation). This assumption implies that, on large samples, the histogram of forecast errors should follow the pattern of a normal distribution centered at zero. If the histogram is observed severely skewed, the violation of the assumption should be investigated. One typical method to verify whether the forecast errors are normally distributed is the use of normal probability plots. A normal probability plot is a scatter diagram of the forecast errors over the standard residuals, which are calculated by:

$$Z_i = \frac{e_i}{S_e} \tag{2}$$

$$e_i = Y_i - \hat{Y}_i \tag{3}$$

where:

e_i = residual of the ith observation

S_e = standard deviation of the estimated residuals

If the forecast errors follow a normal distribution, a straight line should be observed in the probability plot of residuals. Another method for normality test is to compute the Jarque-Bera statistic. The details about this test can be found in [17]. The histogram combined with normal probability plot of forecast errors is adopted in this analysis using the linear regression procedure available in SPSS.

Ordinary least squares analysis also assumes that the individual value of the dependent variable is not affected by each other, i.e. no autocorrelation. The violation of this assumption frequently occurs in regression models using time-series data. Autocorrelation of the residuals causes the estimate of the residuals variance to be small; therefore an unreliable evaluation may result [6]. One widely used method to check the presence of the autocorrelation is the Durbin-Watson test. The Durbin-Watson (D-W) *d*-statistic is calculated to determine whether the correlation between residuals is statistically equal to zero. The range of the D-W *d*-statistic is always within 0 and 4. Values close to 2 indicates that autocorrelation doesn't exist. Values close to 0 and 4 indicates positive and negative autocorrelation, respectively. More information about decision of rules for the D-W test can be found in [18]. Autocorrelation in the residuals can also be examined by plotting of residuals versus time (called time plot of residuals). The time plot of the residuals should not display any discernible trend if autocorrelation is not present. Both the D-W test and the time plot of residuals are available in SPSS. The D-W test is used in this analysis.

The last assumption supporting the regression analysis to yield valid least-square estimates is the constant variance of residuals, i.e., homoscedasticity. Residuals with non-constant variance are said to be heteroscedastic, which distorts the measure of unexplained variation, thus misleads the standard goodness-of-fit statistic R^2 and *t*-tests (both of them will be introduced later in this chapter) [6]. This heteroscedastity can be tested by plotting residuals either over time or against the estimated values of the dependent variable. The latter method is employed in this analysis. If the variances show no discernible pattern, the homoscedasticity assumption is verified.

B. Statistical Tests of the Regression Coefficients

Once the regression model for international air passenger forecast has been calibrated and tested for the underlying assumptions of the linear regression models. A graph of the observed data vs. the forecasted value is generated to determine how well the model works. It is also necessary to perform some statistical tests to examine the forecasting accuracy of model.

Another important task to evaluate the regression model is to examine the statistical validity of the regression coefficients. Appropriate *t*-tests for each regression coefficient should be performed to determine the level of statistical significance. Each coefficient should be analyzed to check whether the estimated sign of the coefficient is consistent with the expectations of the sign. It is also appropriate to evaluate the magnitude of the coefficient to make sure that it is reasonable within the context of the computations.

A *T-test* is used to examine whether each independent variable contributes significantly (i.e. statistically significantly different from zero) to the model in a statistical way. Typically, the *t*-value greater than 2 is considered statistically significant from zero. Therefore statistically meaningful relationships between the dependent variable and the corresponding independent variables can be quantified by examination of the appropriate *t*-value.

The estimated sign of the coefficient should be consistent with the logical expectations of the sign. For example, according to the economic theory, the coefficient for GDP in air travel demand model should be positively related. Similarly, the magnitude of the coefficient should be reasonable within the context of the model. Any explanatory variable with a “wrong sign”, “wrong magnitude” or “statistically insignificant” can be dropped from the regression equation. As previously explained, multicollinearity and violation of constant variance assumption may cause the “wrong sign” of the regression coefficient. Additionally, the “wrong magnitude” might be caused by an error in the data tabulation. It is not surprising that in many cases, a regression equation with an “insignificant” explanatory variable frequently provides a better prediction after the insignificant explanatory variable is omitted. Thus these issues should be considered about variables selected in the final regression equation.

C. Multicollinearity

Multicollinearity is also important to test during the model evaluation because its existence may inflate the variances of the parameter estimates. The multicollinearity occurs when two or more explanatory variables are highly correlated with each other, which leads to unreliable estimates of model. Consequently, the multicollinearity makes the interpretation of the estimated parameters extremely difficult. Usually the explanatory variables with *t*-statistics below the critical value given the sample size and level of confidence should be excluded from the final model. The presence of multicollinearity creates lower *t*-statistics values because the standard errors of the regression coefficients are largely overestimated. Without a multicollinearity evaluation, it is no longer possible to determine which of the independent variables are relevant in the regression equation.

The identification of multicollinearity problem focuses on determining its seriousness more than presence [19]. Independent variables are almost always correlated to some degree, so the influence of multicollinearity on the regression results is a matter of degree. Multicollinearity can usually be identified by the following three approaches: First, checking the logical correlation coefficients between the dependent and independent variables. Significant but 'wrong' sign of regression coefficient between the dependent and independent variables shows severe multicollinearity. A second method is to estimate the correlation matrix for independent variables. High correlation coefficient (0.8 or higher) indicates serious multicolinearity problem. The third approach is to examine the different values of R^2 with leaving out each of the explanatory variables. The small difference change in R^2 indicates a significant multicollinearity or values of the Variance Inflation Factor (VIF, SPSS has it as a multicollinearity diagnostic statistic) exceeding 10 can indicate multicollinearity [20]. In this analysis, a combination of these three methods is used to test multicollinearity. The effect of multicollinearity can be reduced by increasing the sample size and eliminating redundant independent variables. For this reason, the U.S. GDP is excluded from the regression models developed. The U.S. GDP and World Region GDP are found correlated with the dependent variable during the model development.

D. Testing the Estimated Model for Overall Significance

A standard measure of goodness-of-fit used to evaluate regression model is the *F* statistic along with the coefficient of determination R^2 or $R^2{}_{adj}$. The *F*-statistic is used to test whether there is a statistically significant relationship between the dependent and the independent variables (whether all the regression coefficients are zero). The *F* statistic is the ratio of the mean square regression [SSR/ (k-1)] to the mean square error [SSE/ (n-k)]:

$$F = \frac{\sum_{i=1}^{n}(\hat{Y}_i - \overline{Y}_i)^2 /(n-k)}{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 /(k-1)} \tag{4}$$

where:

k = the number of estimated coefficients plus the intercept estimated in the regression (for bivariate regression, it is 2)

n = the sample size

The coefficient of determination can be used to tell how well the model fits the observed data. Whereas the *F* statistic is a useful test of the estimated model's ability to explain any variation in the dependent variable, it does not provide clues about the strength of the explanatory power. The value of R^2 measures the percentage of the variation in the dependent variable Y that is explained jointly by the independent variables X . For example, if R^2 is 0.80, which can be interpreted as 80 percent of the variation in Y can be explained by the estimated model. Although a high R^2 does not necessarily mean an "appropriate" model, an "appropriate" model is expected to have a reasonably "high" R^2 [6]. The better the fit of the regression model, the closer R^2 is to 1.

The R^2 statistic is calculated by comparing the explained variation of the model to the total variation. It is estimated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \overline{Y}_i)^2} \tag{5}$$

where:

Y_i = observed value

$\overline{Y}_i$ = sample mean

$\hat{Y}_i$ = predicated value

n = the sample size

Instead of standard R^2 statistic, the $R^2{}_{adj}$ is employed in the study to measure the goodness-of-fit of the regression model. $R^2{}_{adj}$ is always recommended when comparing two alternative models containing an unequal number of independent variables or two alternative models using different functional forms but the same sets of independent variables [21]. The value of R^2 always increases as the number of independent variables is increased in a regression equation. In other words, the goodness-of-fit of the model appears to improve by adding additional independent variables. Using $R^2{}_{adj}$, the benefits obtained by adding additional independent variables are balanced against the cost of losing additional degrees of freedom. An adjusted R^2 value can be calculated as follows:

$$R^2{}_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \tag{6}$$

where:

R^2 = Coefficient of determination

n = the sample size

p = the number of independent variables included in the air travel demand model

E. Evaluation of Model Forecasts over Historical Periods

The root mean square error (RMSE) is a measure of standard deviation of the forecasting error and is defined as the difference between the observed data and the forecasted value generated by the model. The RMSE statistic is estimated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \tag{7}$$

where:

e_t = the forecast error in time period t

n = the sample size

Two types of *RMSE*s, within-sample and out-of-sample, are usually applied to determine the forecasting accuracy of a model [6]. "Within-sample" *RMSE* is calculated for the alternative models that use the entire available historical data. Whereas, "out-of-sample" *RMSE* can be estimated for the models whose calibration are conducted by portioning the whole observed historical data into two subsets. The first subset is used to calibrate the model and generate the forecast. The forecast is then used to compare not only with the actual data from the first subsets, but also with the observed data from the second subset that is not employed in the model calibration. Because of data limitations, the model presented in this analysis is calibrated with the complete historical data, so only "within-sample" *RMSE* is calculated.

RMSE can be used to select the best forecasting model by simply choosing the model with the smallest *RMSE*. However, it is important to notice that comparisons of *RMSE* for alternative forecasting models using different transformations of the data are not permissible [22].

3.1.4 International Passenger Enplanements Forecast

The forecasts of international passenger enplanements from the U.S. to each World Region are calculated using individual regression models. During this stage, the collected GDP projections of each World Region combined with the defined dummy variable for the Sep. 11, 2001 terrorist attack are inserted into the resulting model separately.

It is assumed that the historical relationship between the passenger enplanements from the U.S. to each World Region and each World Region's GDP may not change over the forecasting horizon. An econometric model that fits well with the historical data to which it is calibrated does not guarantee its future forecasting accuracy. New factors that contribute to international air passenger demand may appear in the future. Based on this uncertainty, it is appropriate to assume that the World Region GDP will be the main variable to explain the international air passenger demand in the future.

3.2 Allocate Air Passengers to Airports

In this stage, the international passenger enplanements forecasted in the first step is allocated to U.S. airports using the air passenger market share of each international airport to each World Region. The historical airport market share is investigated to find any trend that can be used in future projections. The estimated airport market shares are then multiplied by the forecasts of the total U.S. international passenger enplanements to obtain the international passenger enplanements at the airport level.

A market share of an airport to a World Region is defined as the ratio of international passenger enplanements at the airport to the World Region over the total international passenger enplanements from the U.S. to the World Region. An airport market share is given by:

$$MS_{i,k} = \frac{IP_{i,k}}{IP_{US,k}} \approx \frac{IP_{i,k}}{\sum_{i=1}^{66} IP_{i,k}} \tag{8}$$

where:

i = Airport (66 U.S. international airport, please see details in Table 1);

k = World Region (Africa, Asia; Canada, Central America & Caribbean, Europe, Mexico, Middle East, Oceania, South America and U.S.)

$MS_{i,k}$ = Market share of airport i to World Region k;

$IP_{i,k}$ = International passengers from airport i to World Region k;

$IP_{US,k}$ = Total international passengers from the U.S. to World Region k.

3.2.1 Data Collection

To track the trend of an airport market share, the historical market share data between 1990 and 2004 is collected from T-100 international segment data [2]. Data filtering and pre-processing are necessary to obtain the data in the appropriate form, thus Microsoft Access is used to process the historical market share data. Figure 12 graphically shows the data collection procedure.

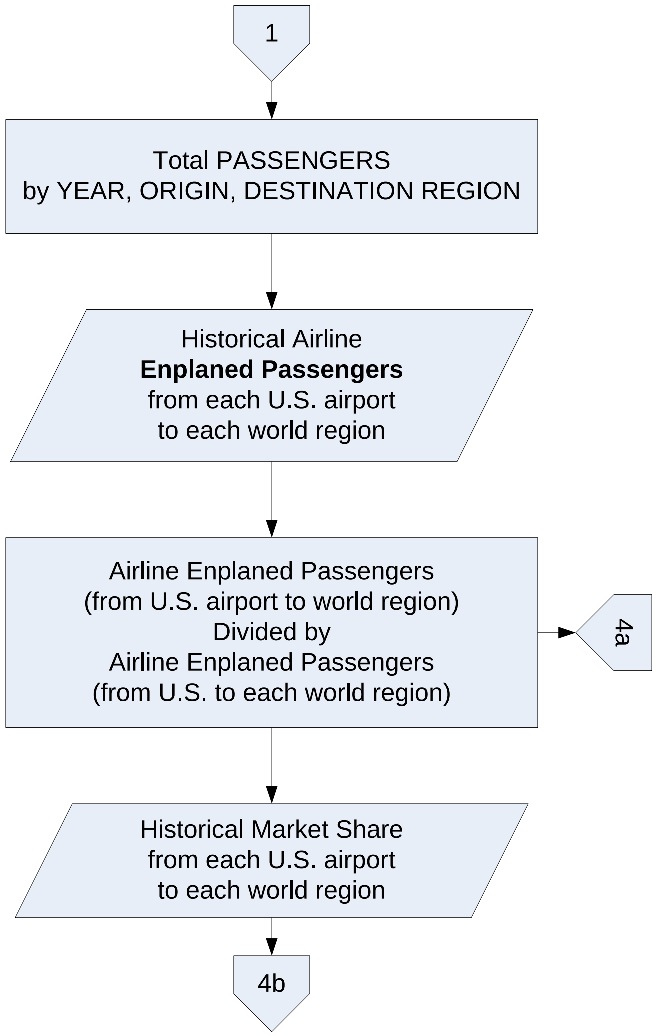
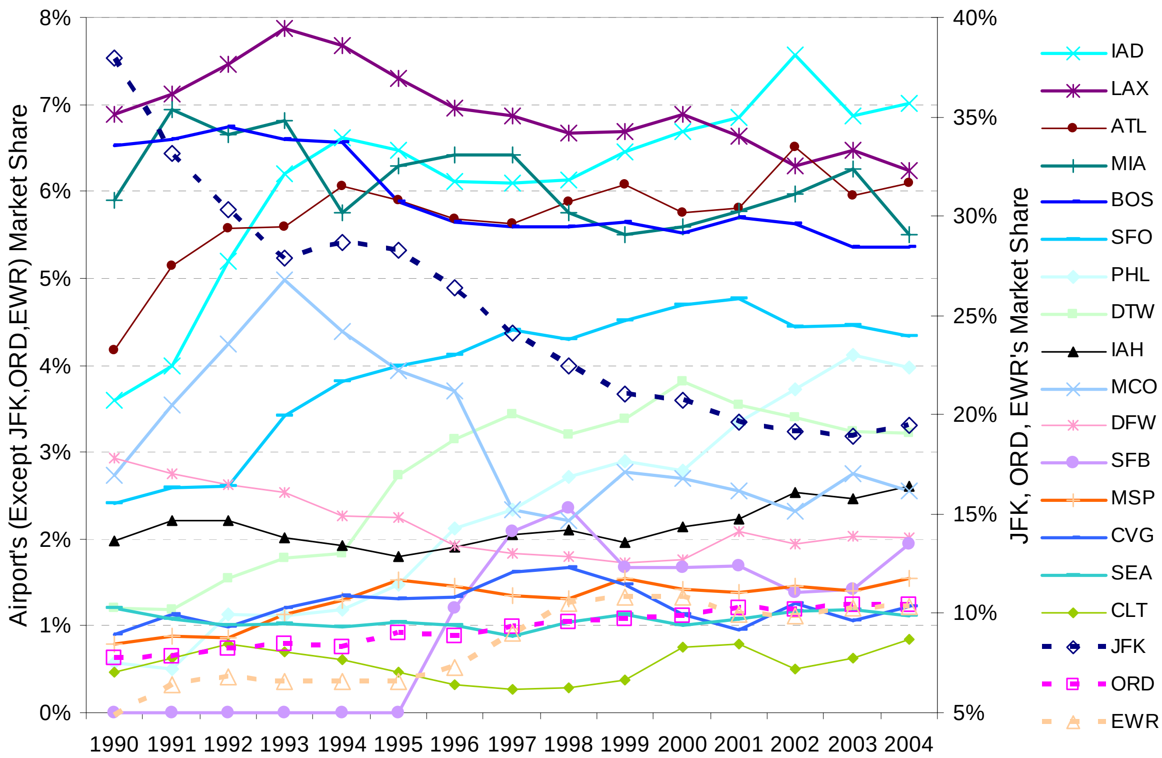


Figure 12. Flowchart - Historical Market Share Data Collection.

3.2.2 Analysis of Historical Trend of the Market Share

The socio-economic characteristics of each airport's catchment area are not found to be highly correlated with the airport's market share. The first step of the airport market share analysis is to plot the trend over the historical period. Figure 13 shows the market share trend of the top nineteen U.S. airports with flights to Europe. The top nineteen U.S. airports with flights to Europe account for 95% of total passenger enplanements from the U.S. to Europe.

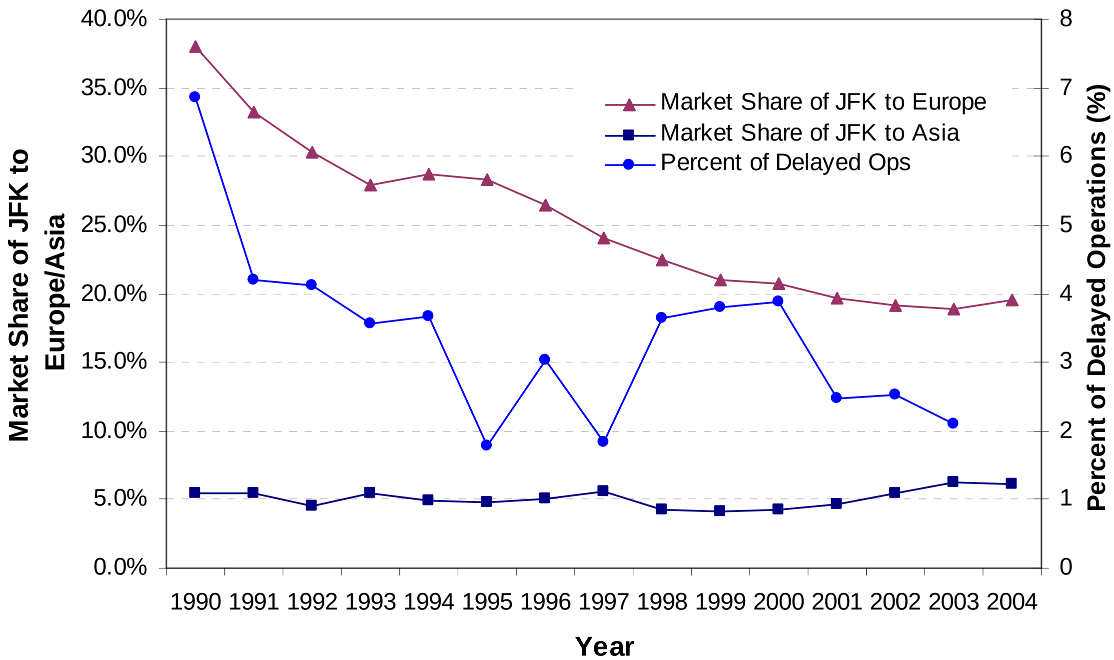


Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 13. Historical Trend of Market Share for Top 19 Airports to Europe.

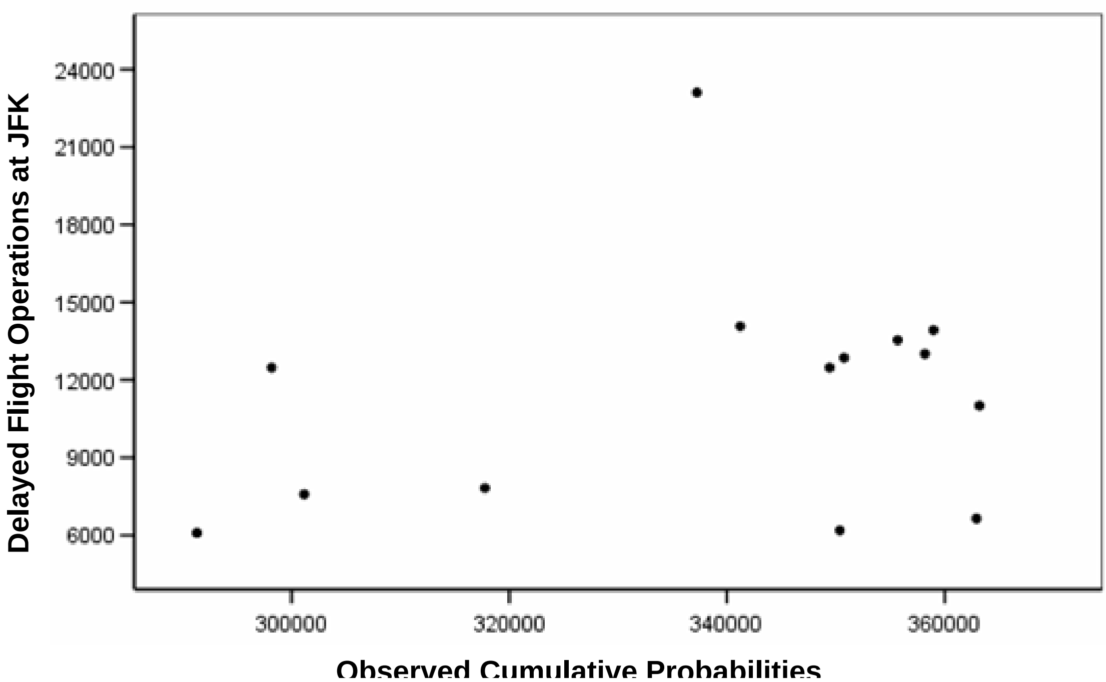
It is noted that JFK's airport market share decreased drastically from 38% to 19% during the period spanning from 1990 to 2004. On the other hand, EWR's airport market share increased from 4.9 % to 10.4 % during the same period. Considering the fact that geographically, JFK and EWR almost share the catchment area of the international air passenger demand, it is very hard to explain the opposite trend of the two airports' market share solely with their catchment area's socio-economic data.

According to previous studies, the airport's level of service is another significant supply variable frequently used in air travel demand models. The relationship between the airport's market share and level of service such as the percent of delayed operations is shown below.



Source: Federal Aviation Administration (FAA), Operational Network (OPSNET), http://www.apo.data.faa.gov/.

Figure 14. Market Share of JFK to Europe & Percent of Delayed Operations.



Source: Federal Aviation Administration (FAA), Operational Network (OPSNET), http://www.apo.data.faa.gov/.

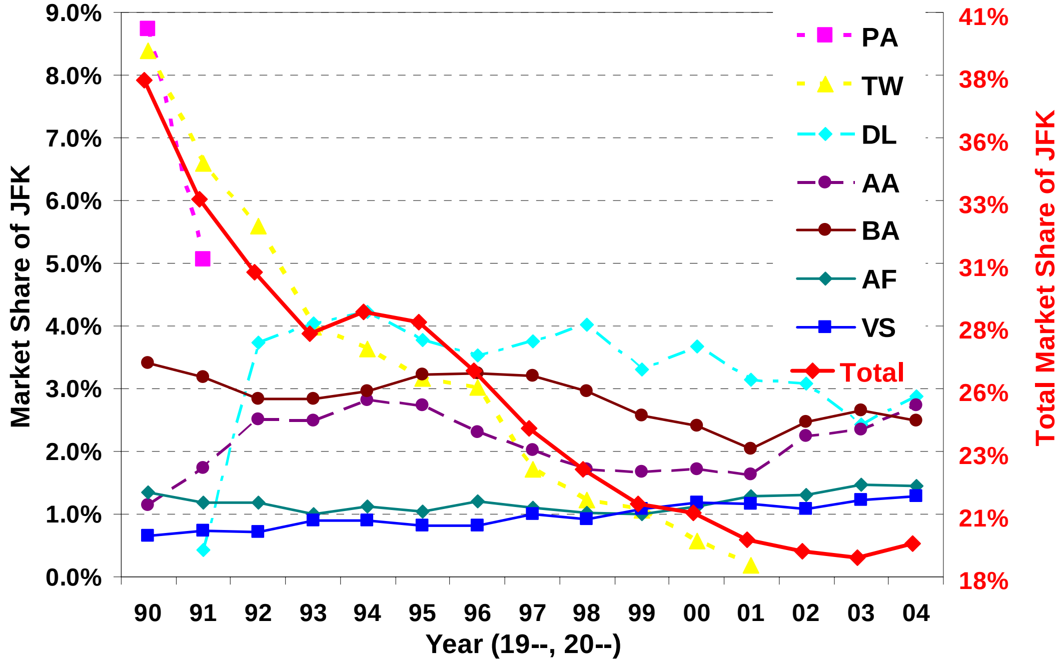
Figure 15. Total Flight Operations V.S. Percent of Delayed Operations.

Table 6. Correlation Coefficients between Total Operations and Percent of Delayed Operations at JFK airport

		Ops_Total_JFK	Ops_Delayed_JFK
Ops_Total_JFK	Pearson Correlation	1	.253
	Sig. (2-tailed)		.384
	N	14	14

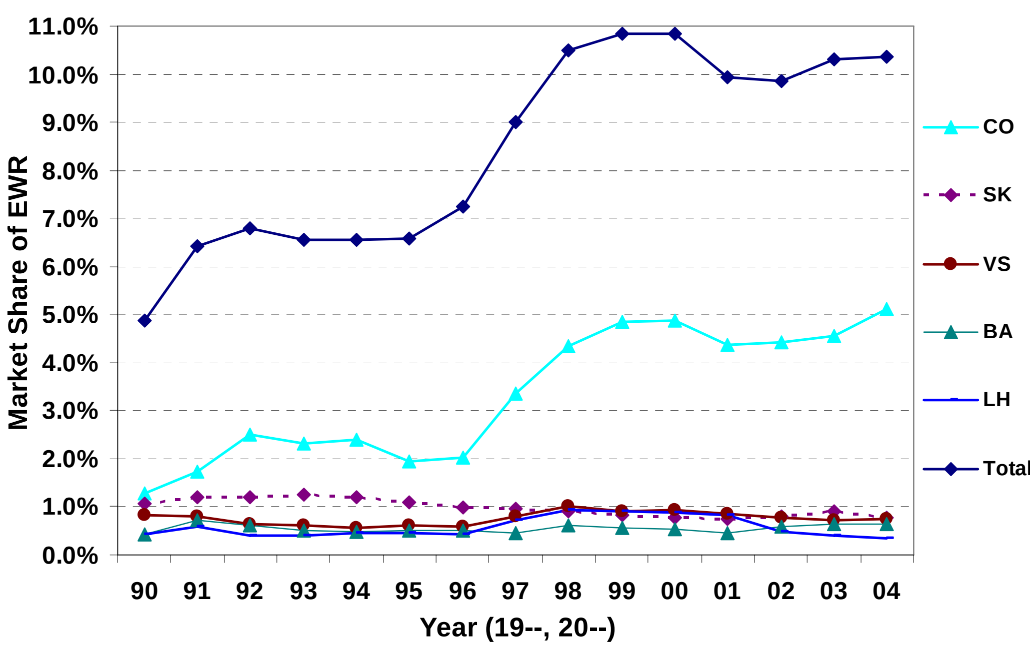
As an important indicator of level of service, the percent of delayed flights at an airport could be related to the airport market shares. One reasonable conjecture is that passenger may avoid to travel through congested airports, which could result in a decreased market share at such airports in the future. As shown in Figure 14, any trend is not observed between the market share at JFK to Europe (or Asia) and the percent of delayed operations at JFK. The scatter plot is constructed further to check the relationship between the percent of delayed operations and the total operations at JFK as displayed in Figure 15. No correlation is found between the percent of delayed operations over time at each airport and the historical airport market share data. Table 6 shows that there is no significant relationship between them. Based on the above analysis, it is concluded that both socio-econometric characteristics of airport catchment area and level of service at airport cannot explain the large change in airport market share at airports such as JFK and EWR.

Further analysis suggests that the market share fluctuation over time can only be explained by airline bankruptcies or mergers. Research is carried out on the airline's business shares at JFK and EWR airports to Europe during the historical period from 1990 to 2004. In this analysis, the airline business market is defined as the ratio of one airline's passenger enplanements at the airport of interest to a World Region, relative to the total passenger enplanements from the U.S. to a World Region. The business share of top airlines at JFK and EWR to Europe are collected from T-100 international segment data. As stated before, T-100 international segment data includes the specific flight information for each carrier. A plot of the top airline's business share at JFK and EWR to Europe over time is shown in Figures 16 and 17, respectively (the major airlines offering flights to Europe at JFK and EWR airports are listed in Table 7 as reference).



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 16. Business Shares of Major Airlines Offering Flights to Europe at JFK Airport.



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 17. Business Shares of Major Airlines Offering Service to Europe at EWR Airport.

Table 7. List of Major Airlines Offering Service to Europe at JFK and EWR Airports.

CARRIER	CARRIER_NAME
AA	American Airlines Inc.
AF	Compagnie Nat'l Air France
BA	British Airways Plc
CO	Continental Air Lines Inc.
DL	Delta Air Lines Inc.
LH	Lufthansa German Airlines
PA	Pan American World Airways
SK	Scandinavian Airlines Sys.
TW	Trans World Airlines Inc.
UA	United Air Lines Inc.
VS	Virgin Atlantic Airways

As shown in Table 7, the market share of New York JFK airport to Europe decreased from 38% to 19% during the period 1990-2004. Over the same period, the market share of New York Newark Airport (EWR) increased from 4.9% to 10.4%. During the early period of the analysis Pan America World Airway and Trans World Airline were once main airlines at JFK to Europe in 1990, but they disappeared from JFK airport after 1993 because of their bankruptcies. Furthermore, Figure 16 indicates that the decrease of JFK's market share to Europe can be explained well by the trend of combined business share of Pan America World Airway and Trans World Airline at JFK to Europe. Similarly, Figure 17 shows that the trend of EWR's market share to Europe can be explained mainly by the business share of Continental Air Lines at EWR to Europe.

From the analysis, it is concluded that one of the most important factors influencing airport market share is the airline business rather than socio-economic situation of the catchment area or airport delays. However, it should be pointed that forecasting future airline business is a complex analysis beyond the scope of this report. For this reason, it is decided to apply the airport market share in year 2004 to all future years in our analysis.

3.3 Converting Air Passengers to Flight Operations at Airports

In this step, the forecasted passenger enplanements at each airport are converted to flight operations. The assumed average seats per aircraft and load factor from each airport to each world are used in the conversion process. The load factor is the percentage of airline seats that are occupied by passengers. The steps involved in this procedure are the following ones:

1. Review the trend of historical average seats per aircraft and load factors from each airport to each World Region during the period of 1990 to 2004,
2. For each forecast year, define different scenarios of average seats per aircraft and load factor at each airport for each World Region,
3. Apply the assumed average seats per aircraft and load factor to convert passenger enplanements to passenger operations at each airport to each World Region, and
4. Conduct sensitivity analysis for flight operations with various scenarios of average seats per aircraft and load factor.

The average seats per aircraft for a given airport and a given World Region is calculated by dividing the total seating capacity by the total flight operations supplied from the airport to the World Region. Load factor is the percentage of total international passenger enplanements to the total available seats from an airport to a World Region.

Average seats per aircraft and load factor are defined individually for each airport to each World Region. Each aircraft type has different capabilities in range and capacity, and airlines determine appropriate aircraft types according to the air passenger demand and range of the flight, so it is necessary to examine the historical trend of average seats per aircraft and load factor by World Region at each airport. To check whether differences exist between the national and airport level average seats per aircraft and load factors, several paired sample *t*-tests are conducted. The paired sample *t*-test is used to test the hypothesis that no difference exists between two variables. Tables 8 and 9 compare the national level average operational factors, i.e. average seats per aircraft and load factor from the U.S. to Europe with the corresponding data from the top four airports (JFK, ORD, EWR and IAD) to Europe.

Table 8. Load Factor and Average Seats/Aircraft from Top 4 U.S. Airports to Europe.

Year	Average Seats (AS) per Aircraft to Europe					Load Factor to Europe				
	Total	JFK	ORD	EWR	IAD	Total	JFK	ORD	EWR	IAD
1990	296.9	305	267	265	274	67.1%	66%	59%	70%	65%
1991	307.3	311	258	308	247	61.8%	61%	57%	63%	67%
1992	300.8	296	256	296	286	61.2%	59%	59%	61%	65%
1993	277.7	270	242	286	271	65.4%	62%	64%	62%	69%
1994	285.5	284	246	286	278	66.4%	63%	66%	67%	68%
1995	298.6	304	264	282	290	66.3%	60%	65%	69%	71%
1996	302.3	306	264	284	289	65.9%	60%	66%	68%	70%
1997	291.8	286	266	272	290	70.1%	66%	68%	72%	73%
1998	264.9	250	244	247	277	76.9%	74%	73%	77%	74%
1999	265.8	254	246	246	281	76.1%	73%	71%	74%	77%
2000	267.9	252	248	252	281	77.8%	75%	75%	77%	75%
2001	261.1	254	241	240	260	74.2%	72%	72%	73%	74%
2002	255.5	247	239	231	248	78.8%	77%	79%	79%	77%
2003	256.5	254	239	229	250	79.0%	77%	79%	78%	78%
2004	258.3	256	242	230	254	81.0%	80%	80%	81%	80%

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Table 9. Paired Sample Test of Average Seats/Aircraft at Top 4 Airports to Europe.

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	AS_Total - AS_JFK	4.12667	7.237	1.869	.11908	8.134	2.21	14	.044
Pair 2	AS_Total - AS_ORD	28.59333	11.04	2.850	22.48	34.71	10.0	14	.000
Pair 3	AS_Total - AS_EWR	15.79333	11.77	3.039	9.276	22.31	5.20	14	.000
Pair 4	AS_Total - AS_IAD	7.66000	17.97	4.640	-2.293	17.61	1.65	14	.121

3.3.1 Data Collection

Both the historical average seats per aircraft and load factors during the period 1990 to 2004 are collected from T-100 international segment data. Figure 18 illustrates the data collection procedure applied in this analysis.

The average seats per aircraft and the load factor are user-defined parameters in the model developed. To make sure that the defined values are reasonable and consistent with the historical values, the trend of historical average seats per aircraft and load factor are analyzed. The historical average seats per aircraft and load factors over the period of 1990 to 2004 for each airport-World Region pair are estimated using T100 international segment data. The historical trend over time and the spatial distributions of both variables are available as a reference to the user of the model.

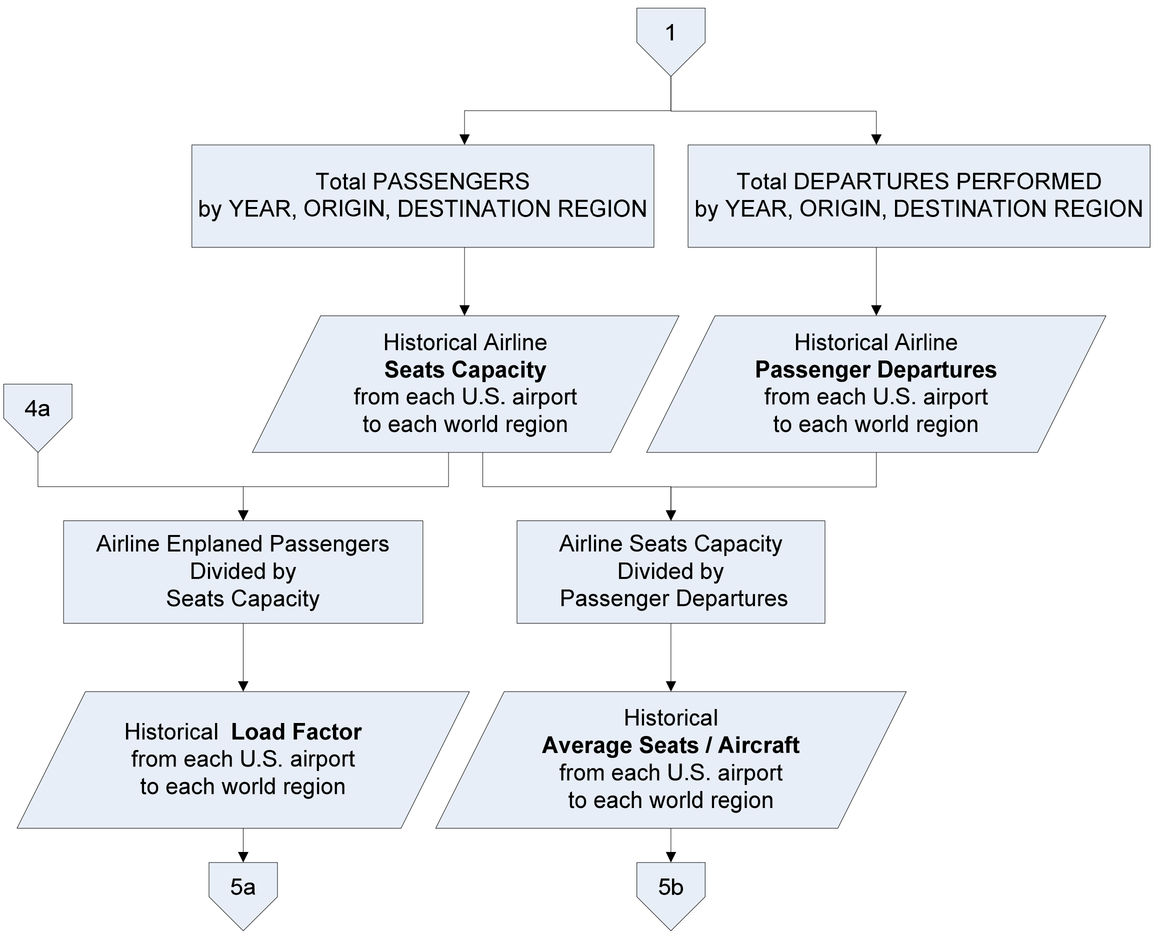
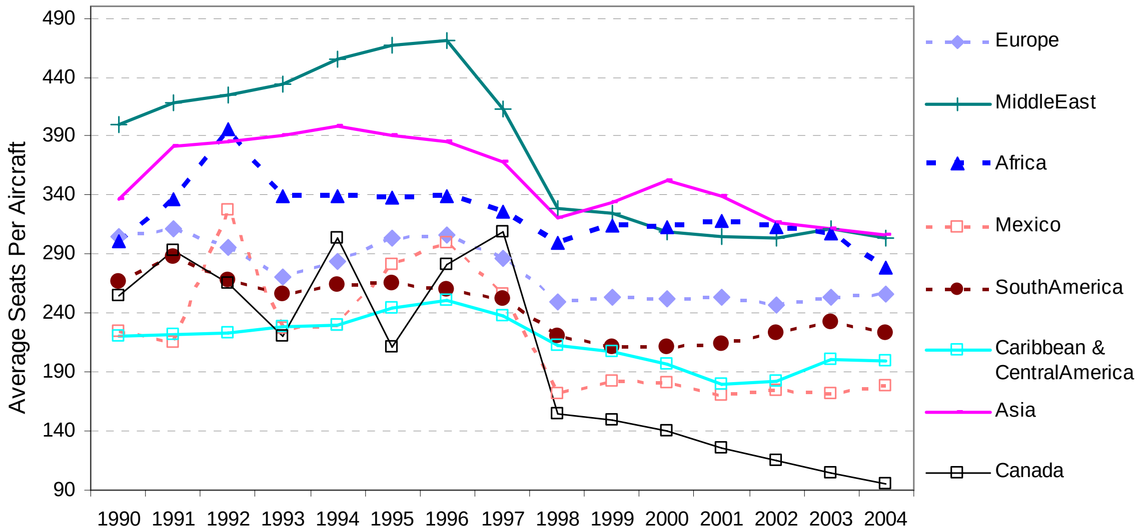
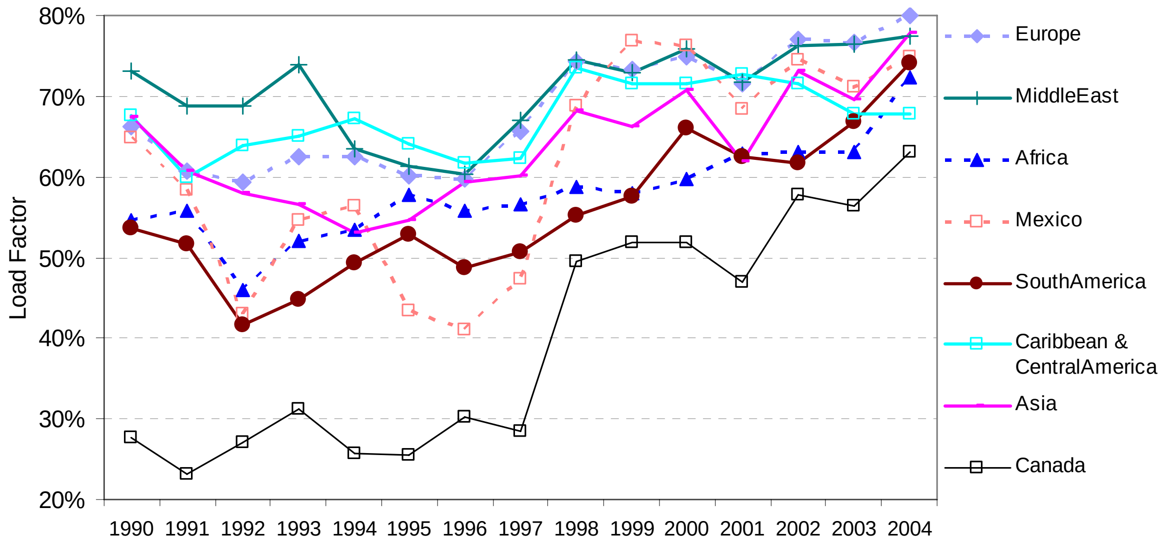


Figure 18. Flowchart - Historical Average Seats per Aircraft and Load Factor Data Collection.



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 19. Average Seats per Aircraft of International Passenger Flights from JFK to all World Regions.



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 20. Load Factor of International Passenger Flights from JFK to all World Regions.

3.3.2 Analysis of Historical Trend of Average Seats per Aircraft and Average Load Factor

It is observed in Figures 19 and 20 that the average seats per aircraft remained stable at JFK airport after 1998 (except Canada). However, the average seats per aircraft decreased during the period between 1997 and 1998. The mainstream use of extended-range, twin-engine operations (ETOPS) approved by the FAA and the European Joint Aviation Authority (JAA) might help explain this trend [23]. The load factors from each airport to each World Region fluctuated widely during the period 1990-2004. An increasing trend is observed as shown in Figure 20. The load factor increased noticeably during the period 1997-1998, which conforms to the decreasing average aircraft size during the same period as shown in Figure 19.

Chapter 4 Results and Discussions

4.1 National Level Forecast

4.1.1 Model Development and Evaluation Results

Table 10 presents the estimated regression equations to forecast the passenger enplanements from the U.S. to each World Region. The statistical validity and forecast accuracy of all the regression models is found to be acceptable through the tests discussed in Chapter 3.

The underlying assumptions of the regression analysis are found to be valid using the residual analysis for all the models developed. The tests for these validations are: the histogram of residuals and normal probability plot of the standardized residuals are combined to test the assumption of normal distribution with a mean of zero. The plots of standardized residuals versus the standardized predicted values of each model are used to verify the homoscedasticity assumption. The critical Durbin-Watson statistic values are checked to support the nonautocorrelation assumption. Furthermore, the VIF value less than 10 is helpful to exclude any multicollinearity problems. All regression coefficients for each explanatory variable are also tested statistically significant. The signs of each explanatory variable match the underlying economic theory and expected magnitudes. Finally, acceptable R^2_{adj} values and statistically significant F static values prove that all the estimated models are reliable to forecast the passenger enplanements from the U.S. to each World Region.

Since each individual regression model is developed to forecast the passenger enplanements from the U.S. to each World Region, the evaluations are conducted separately for each model. The regression model and the model evaluation for Europe are presented here as an example.

Detailed information about the estimated model to predict the passenger enplanements from the U.S. to Europe is presented in Table 11. The corresponding tables for all other estimated models are included in Appendix C. The residual analyses for the U.S. to Europe model evaluation are also shown in Figures 21, 22 and 23.

The model summary in Table 11 shows an acceptable R^2_{adj} value of 0.954 for the regression equation, which confirms the assumption that Europe GDP is a main contributor to the air travel demand between the U.S. and Europe. The coefficients sub-table indicates that the expected number of passenger enplanements from the U.S. to Europe is equal to 33,017,325 + 6.609* $\mathrm{GDP}_{\mathrm{Europe\_t}}$ - 6,297,754 D_{911_t} . In this equation: the unit of Europe GDP is in millions of 2000 U.S. dollars. All the coefficients are calculated statistically different from 0 (i.e., the significance level of *t*-statistic is less than 0.05). Both signs of the explanatory variables match economic theory expectations. The positive sign of the coefficient for Europe GDP is reasonable in that an increase in Europe GDP will cause growth in air passenger demand between U.S. and Europe. In addition, the negative coefficient of the dummy variable implies a deduction in international air travel demand between U.S. and the rest of the world caused by Sep. 11, 2001 terrorist attack.

The ANOVA sub-table summarizes the results of the model from statistical perspective. The regression row in Table 11 gives information about the variation explained by the estimated regression model. The residual row shows the variation that the model fails to account; the significance value of the *F* statistic is less than 0.05, which indicates that the variation accounted by the estimated model is not by chance.

Table 10. Regression Equations to Forecast Air Passenger Enplanements from the U.S. to each World Region.

World Region	Selected Regression Equation [*t*-statistic*]	Adjusted R-Square
Africa	$APT_{U.S.\_Africa\_t} = \underset{[-7.2]}{-11{,}595{,}219} + \underset{[-7.3]}{907{,}889}\, LnGDP_{Africa\_t} - \underset{[-3.5]}{132{,}533}\, D_{911\_t}$	0.829
Asia	$APT_{U.S.\_Asia\_t} = \underset{[-2.8]}{-5{,}767{,}990} + \underset{[7.4]}{2.182}\, GDP_{Asia\_t} - \underset{[-4.6]}{2{,}927{,}403}\, D_{911\_t}$	0.795
Canada	$APT_{U.S.\_Canada\_t} = \underset{[-2.0]}{-1{,}647{,}709} + \underset{[10.9]}{15.297}\, GDP_{Canada\_t} - \underset{[-3.9]}{1{,}158{,}067}\, D_{911\_t}$	0.929
Caribbean & Central America	$APT_{U.S.\_Caribbean\ \&\ Central\ America\_t} = \underset{[-4.7]}{-2{,}205{,}883} + \underset{[22.0]}{61.215}\, GDP_{Caribbean\_t}$	0.972
Europe	$APT_{U.S.\_Europe\_t} = \underset{[-9.6]}{-33{,}017{,}325} + \underset{[14.9]}{6.609}\, GDP_{Europe\_t} - \underset{[-7.4]}{6{,}297{,}754}\, D_{911\_t}$	0.954
Mexico	$APT_{U.S.\_Mexico\_t} = \underset{[-5.6]}{-3{,}900{,}780} + \underset{[14.6]}{21.238}\, GDP_{Mexico\_t} - \underset{[-3.3]}{744{,}085}\, D_{911\_t}$	0.961
Middle East	$APT_{U.S.\_Middle\ East\_t} = \underset{[-7.7]}{-941{,}441} + \underset{[12.0]}{1.684}\, GDP_{Middle\ East\_t} - \underset{[-6.2]}{267{,}846}\, D_{911\_t}$	0.921
Oceania	$APT_{U.S.\_Oceania\_t} = \underset{[-4.2]}{487{,}844} + \underset{[7.7]}{2.032}\, GDP_{Oceania\_t}$	0.807
South America	$APT_{U.S.\_South\ America\_t} = \underset{[-10.4]}{-4{,}599{,}310} + \underset{[18.0]}{7.000}\, GDP_{South\ America\_t} - \underset{[-6.5]}{726{,}633}\, D_{911\_t}$	0.961

*: *The value within the square bracket is t-statistic value for the regression coefficient.*

Table 11. Details of Estimated Model to Forecast Air Passenger from U.S. to Europe.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.980[a]	.960	.954	852206.137	2.293

a. Predictors: (Constant), Europe_GDP, Dummy

b. Dependent Variable: Europe_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-33017325	3448535		-9.574	.000		
	Dummy	-6297754	856190.7	-.727	-7.356	.000	.338	2.96
	Europe_GDP	6.609	.443	1.476	14.926	.000	.338	2.96

a. Dependent Variable: Europe_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.1E+014	2	1.056E+014	145.368	.000[a]
	Residual	8.7E+012	12	7.263E+011		
	Total	2.2E+014	14			

a. Predictors: (Constant), Dummy, Europe_GDP

b. Dependent Variable: Europe_Pax

Final Model:

$$APT_{U.S.\_Europe\_t} = -33{,}017{,}325 + 6.609 GDP_{Europe\_t} - 6{,}297{,}754 D_{911\_t}$$

Where:

$APT_{U.S.\_Europe\_t}$ = Total Air Passengers from U.S. to Europe in Year *t*

GDP_{Europe_t} = Europe Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for Sep. 11, 2001 Terrorist Attack in Year *t* (for $t < 2001$, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Figure 21 presents the normal probability plot of standardized residuals generated by the estimated model. The plot clearly displays the normal distribution of regression residual because it follows the 45 degree line very well. A frequency histogram of the same residuals is plotted in Figure 22. The figure further indicates that no skewness occurs about the mean, which satisfies the assumption that the mean of the regression residual is zero.

To examine the assumption of homoscedasticity, a plot of standardized residuals against the standardized predicted values is graphically shown in Figure 23. No apparent trend is observed in this graph and all residuals fall within a horizontal band located two standard deviations from the zero mean.

Table 12 shows that the lower and upper critical values of the Durbin-Watson statistic for fifteen observations, two explanatory variables at five percent significance level are 0.95 and 1.54, respectively. The Durbin-Watson statistic value of 2.29 ($1.54 < 2.29 < 2.46 = 4 - 1.54$) in the model summary in Table 11 provides the evidence to reject the autocorrelation associated with the residual test. Finally, a VIF value of 2.96 in the Coefficients of Table 11 corroborates no multicollinearity problem.

Table 12. Durbin-Watson Critical Values (Non-Autocorrelation Test).

		X variables, excluding the intercept									
Observations		1		2		3		4		5	
N	Prob.	D-L	D-U	D-L	D-U	D-L	D-U	D-L	D-U	D-L	D-U
15	0.05	1.08	1.36	0.95	1.54	0.82	1.75	0.69	1.97	0.56	2.21
	0.01	0.81	1.07	0.7	1.25	0.59	1.46	0.49	1.70	0.39	1.96

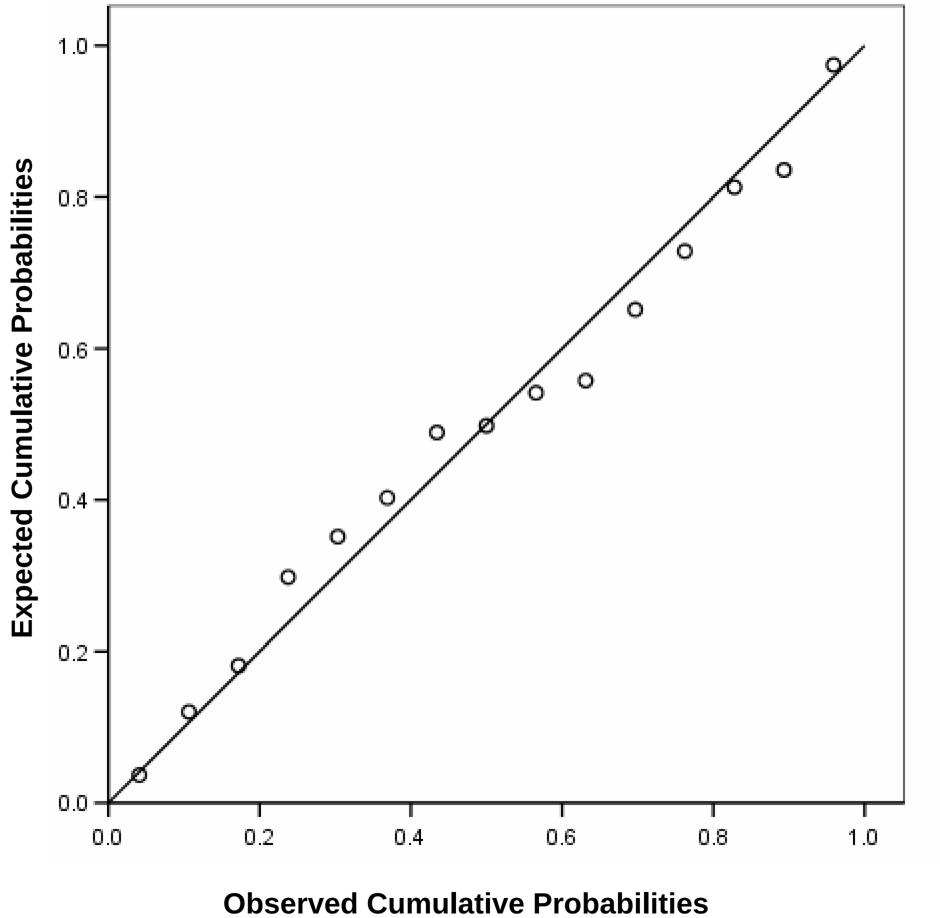


Figure 21. Normal Probability Plot of Regression Standardized Residual (Normality Test - Model to Forecast Air Passengers from U.S. to Europe).

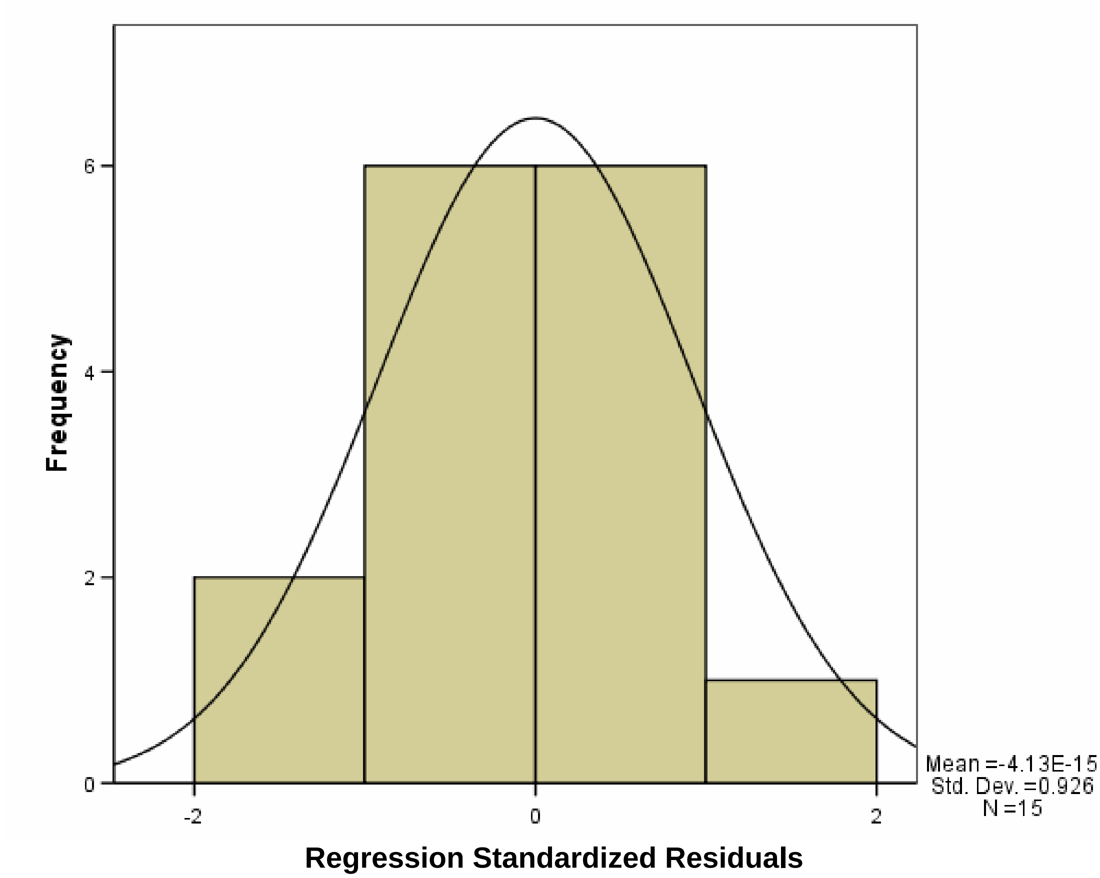


Figure 22. Frequency Histogram of Regression Standardized Residual
(Zero Mean Test - Model to Forecast Air Passenger from U.S. to Europe).

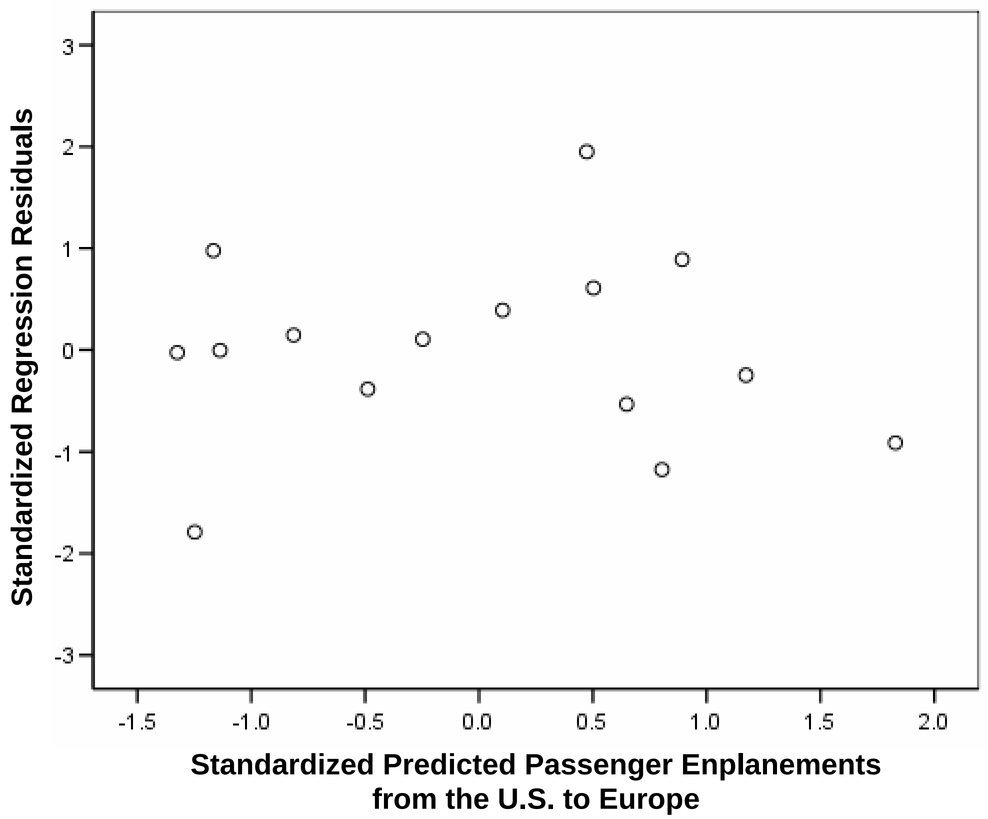
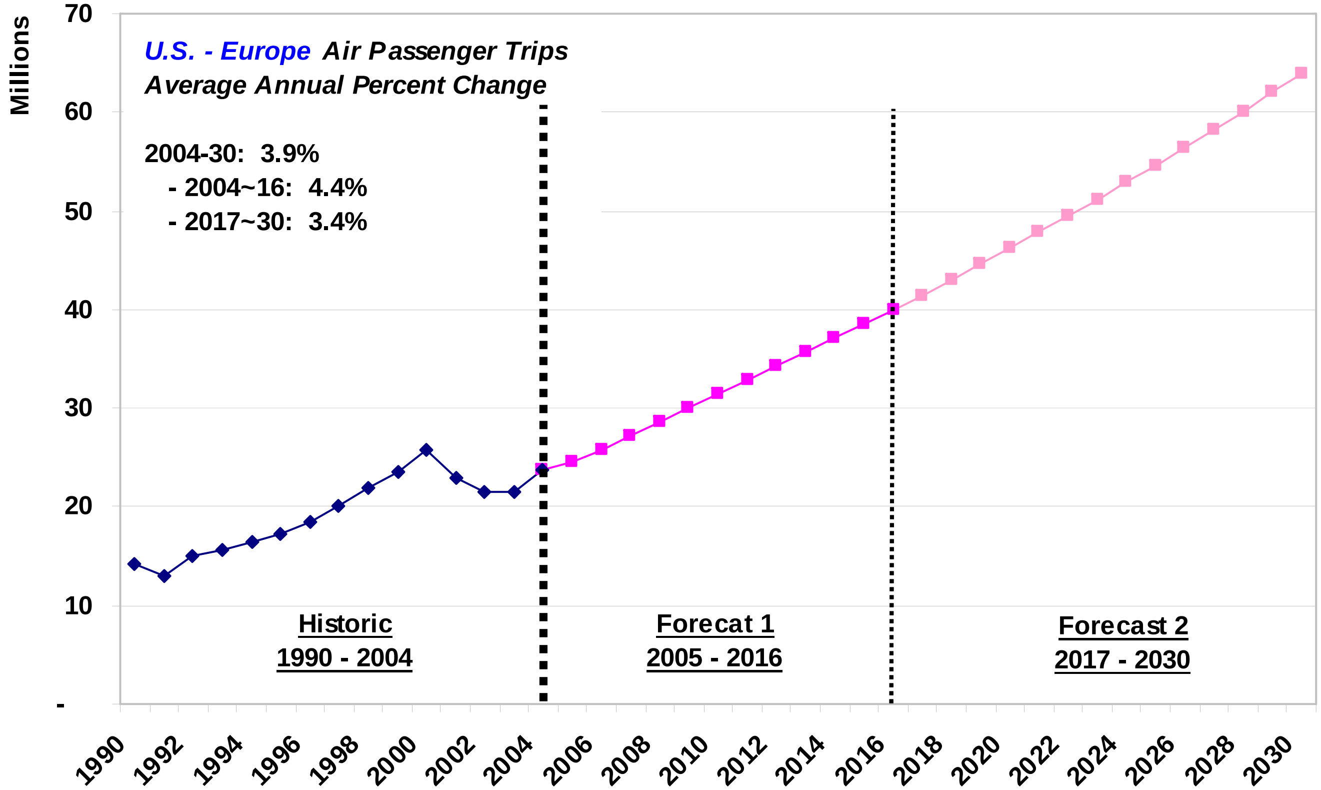


Figure 23. Regression Standardized Residual V.S. Standardized Predicted Value (Homoscedasticity Test - Model to Forecast Air Passenger from the U.S. to Europe).

4.1.2 Forecast Results of Passenger Enplanements from the U.S. to each World Region

The forecasts of passenger enplanements from the U.S. to each World Region are produced by applying the estimated models individually. The resulting forecasts are shown in Tables 13 and 14. The international passenger enplanements from the U.S. to Europe are projected to increase at an average annual rate of 3.9 percent from 23.75 million in year 2004 to 63.97 million in 2030. The growth is faster in the near-term 2004~2016 with an average 4.4% annual change than 3.4% over the period of 2017 to 2030. As shown in Figure 24, the forecast trend is consistent with the historical trend. The average annual growth of international passengers from the U.S. to Asia during 2004 to 2030 is forecasted to be 5.6 percent. The highest growth rates are predicted for the Middle East at 7.7% per year, 6.0% for South America and 5.7% for Africa. This can be explained by their relatively underdeveloped air travel demand markets today.



Source: Historical (1990-2004) Data: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov.

Figure 24. Both Historical and Forecast Passenger Enplanements from the U.S. to Europe.

Table 13. Historical and Forecast Passenger Enplanements from the U.S. to each World Region.

Year	Europe	Africa	Middle East	Canada	Asia	Oceania	South America	Caribbean & Central Camerica	Mexico	Total
1990	14,236,619	93,256	272,998	6,686,221	6,921,660	1,180,032	1,873,048	6,000,332	4,918,602	42,182,768
1991	13,032,798	87,741	289,015	6,104,449	6,850,355	1,164,494	2,064,972	6,084,958	5,140,737	40,819,519
1992	14,984,234	125,765	337,487	6,454,628	7,638,951	1,207,249	2,387,481	6,181,456	5,482,372	44,799,623
1993	15,707,676	142,991	374,925	6,513,949	7,861,951	1,227,403	2,719,399	6,893,246	5,494,245	46,935,785
1994	16,368,294	173,721	440,728	6,415,064	8,765,578	1,223,365	3,049,244	6,914,268	5,696,279	49,046,541
1995	17,182,886	225,249	550,093	6,982,548	9,921,310	1,279,100	3,525,938	7,349,025	5,567,783	52,583,932
1996	18,536,009	255,957	601,123	7,690,269	10,749,955	1,351,267	3,618,815	7,359,170	6,345,073	56,507,638
1997	20,140,153	299,493	608,421	8,072,931	11,215,034	1,336,430	4,038,897	7,562,965	6,890,303	60,164,627
1998	21,877,589	296,902	659,661	8,439,888	10,271,658	1,335,846	4,272,178	8,244,687	7,168,019	62,566,428
1999	23,627,497	339,747	732,607	8,649,282	10,669,654	1,458,207	4,198,584	9,070,424	7,694,034	66,440,036
2000	25,732,084	366,258	792,226	9,076,426	11,559,810	1,663,001	4,301,053	9,670,774	8,370,185	71,531,817
2001	22,905,223	354,276	615,962	8,537,700	10,269,315	1,502,264	3,944,233	9,354,333	7,655,390	65,138,696
2002	21,471,529	281,963	551,341	8,480,826	10,064,819	1,435,610	3,509,822	9,428,369	7,379,806	62,604,085
2003	21,526,594	305,867	607,101	8,526,212	8,773,002	1,502,685	3,490,096	10,298,876	7,810,406	62,840,839
2004	23,750,001	304,931	803,779	9,629,240	10,587,193	1,623,315	3,838,378	10,894,814	9,046,488	70,478,139
2005*	24,680,971	348,776	909,679	10,003,084	11,320,096	1,649,873	4,272,763	11,317,749	9,545,687	74,048,678
2006*	25,925,426	392,327	1,013,186	10,376,086	12,068,134	1,685,598	4,651,575	11,734,868	10,063,831	77,911,031
2007*	27,511,665	435,854	1,115,880	10,760,285	12,840,115	1,723,761	5,041,286	12,066,898	10,601,683	82,097,427
2008*	29,077,496	477,437	1,218,395	11,156,003	13,644,760	1,764,439	5,443,520	12,454,144	11,159,988	86,396,182
2009*	30,604,175	516,973	1,323,463	11,563,607	14,484,356	1,806,833	5,861,910	12,941,966	11,739,488	90,842,771
2010*	32,154,838	555,314	1,432,445	11,983,418	15,359,055	1,850,641	6,295,707	13,469,456	12,341,012	95,441,886
2011*	33,714,621	593,136	1,545,797	12,415,834	16,270,936	1,895,914	6,740,417	14,012,923	12,965,388	100,154,966
2012*	35,251,743	630,684	1,663,724	12,861,221	17,228,418	1,942,697	7,202,200	14,572,244	13,613,508	104,966,439
2013*	36,820,455	667,838	1,786,422	13,319,978	18,233,371	1,991,042	7,679,432	15,147,114	14,286,243	109,931,895
2014*	38,389,306	704,843	1,913,783	13,792,487	19,289,428	2,040,999	8,171,021	15,736,370	14,984,548	115,022,785
2015*	39,968,725	741,455	2,046,133	14,279,176	20,399,894	2,092,622	8,678,584	16,341,296	15,709,380	120,257,265
2016*	41,582,623	778,128	2,184,204	14,780,459	21,569,064	2,145,984	9,204,977	16,971,321	16,461,757	125,678,517
Average Annual Growth: 2005-2016	**4.8%**	**8.1%**	**8.7%**	**3.6%**	**6.1%**	**2.4%**	**7.6%**	**3.8%**	**5.1%**	**4.9%**

Source: Historical (1990-2004) Data: United States Department of Transportation, Bureau of Transportation Statistics, T-100 International Segment Data, http://www.transtats.bts.gov/.

Table 14. Historical and Forecast Passenger Enplanements from the U.S. to each World Region (Continued).

Year	Europe	Africa	Middle East	Canada	Asia	Oceania	South America	Caribbean & Central Camerica	Mexico	Total
2017*	43,229,288	814,802	2,328,144	15,296,794	22,784,492	2,201,143	9,750,697	17,623,138	17,242,742	131,271,240
2018*	44,909,382	851,475	2,478,201	15,828,610	24,048,008	2,258,155	10,316,430	18,297,605	18,053,375	137,041,241
2019*	46,623,578	888,149	2,634,636	16,376,380	25,361,515	2,317,087	10,902,932	18,995,395	18,894,846	142,994,518
2020*	48,372,584	924,822	2,797,719	16,940,579	26,726,991	2,378,002	11,510,952	19,717,365	19,768,259	149,137,273
2021*	50,157,093	961,496	2,967,733	17,521,712	28,146,491	2,440,965	12,141,281	20,464,310	20,674,888	155,475,969
2022*	51,977,826	998,169	3,144,974	18,120,268	29,622,156	2,506,048	12,794,738	21,237,211	21,615,944	162,017,334
2023*	53,835,530	1,034,842	3,329,747	18,736,799	31,156,202	2,573,320	13,472,170	22,036,801	22,592,785	168,768,196
2024*	55,730,945	1,071,515	3,522,373	19,371,808	32,750,945	2,642,857	14,174,466	22,864,183	23,606,730	175,735,822
2025*	57,664,838	1,108,189	3,723,187	20,025,877	34,408,783	2,714,731	14,902,529	23,720,152	24,659,222	182,927,508
2026*	59,637,994	1,144,862	3,932,535	20,699,572	36,132,214	2,789,025	15,657,311	24,605,811	25,751,683	190,351,007
2027*	61,651,208	1,181,536	4,150,781	21,393,475	37,923,832	2,865,818	16,439,785	25,522,138	26,885,686	198,014,259
2028*	63,705,299	1,218,209	4,378,303	22,108,181	39,786,337	2,945,196	17,250,966	26,470,175	28,062,760	205,925,426
2029*	65,801,085	1,254,882	4,615,495	22,844,349	41,722,531	3,027,242	18,091,918	27,451,084	29,284,561	214,093,147
2030*	67,939,421	1,291,556	4,862,768	23,602,591	43,735,330	3,112,052	18,963,733	28,465,968	30,552,809	222,526,228
Average Annual Growth:										
2017-2030	**3.6%**	**3.7%**	**5.9%**	**3.4%**	**5.2%**	**2.7%**	**5.3%**	**3.8%**	**4.5%**	**4.2%**
2005-2030	**4.1%**	**5.7%**	**7.2%**	**3.5%**	**5.6%**	**2.5%**	**6.3%**	**3.8%**	**4.8%**	**4.5%**

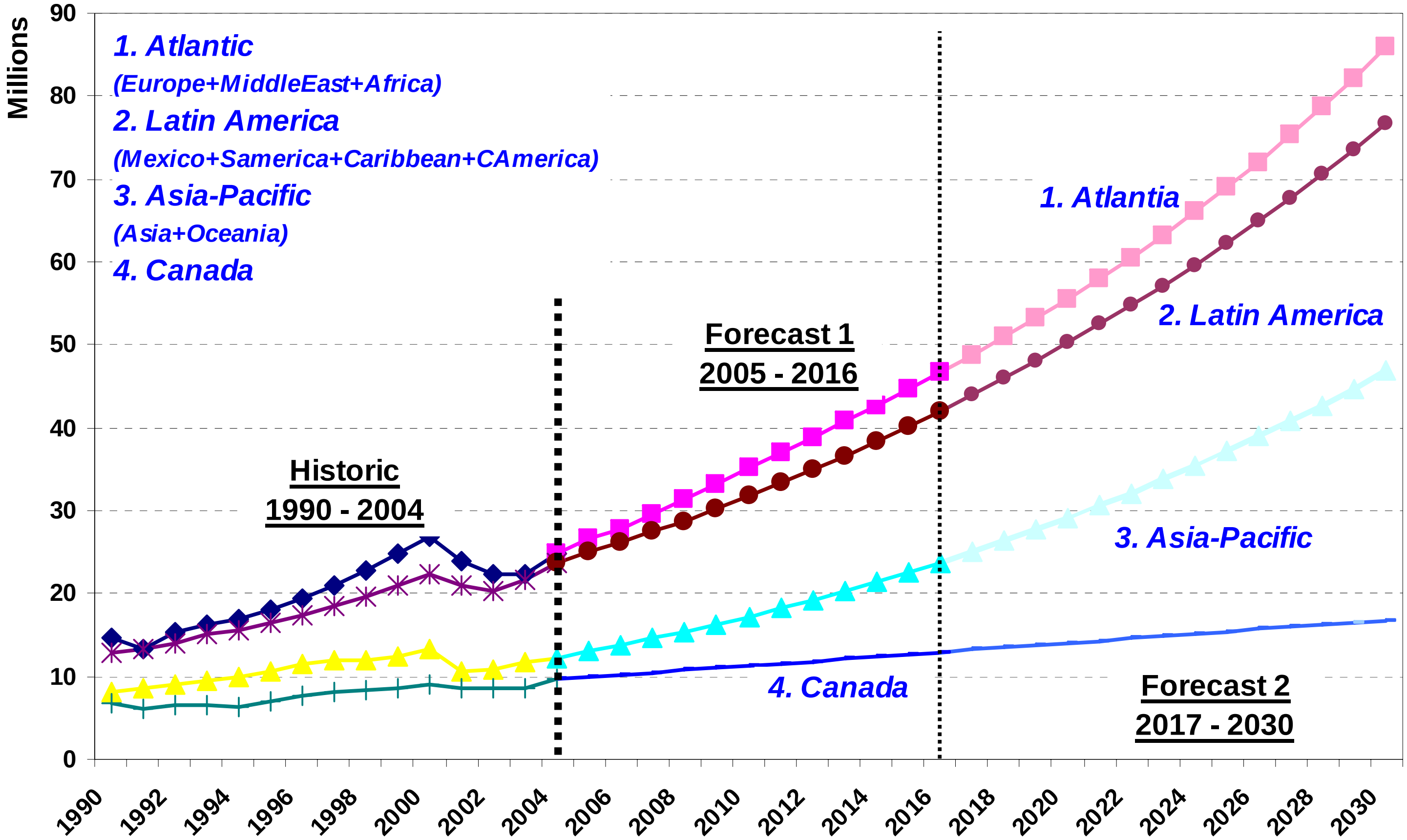
Source: Historical (1990-2004) Data: United States Department of Transportation, Bureau of Transportation Statistics, T-100 International Segment Data, http://www.transtats.bts.gov/.

4.1.3 Evaluation of the Forecast Results

The forecasted trend of international passenger enplanements from the U.S. to each World Region is consistent with the corresponding historical trend. This can be examined in Figure 25.

The forecast of passenger enplanements from the U.S. to each World Region are also compared with FAA aviation forecasts. It is helpful to compare the forecast results with other models using the same metric. As stated in Chapter 2, the FAA, Boeing and Airbus produce their own forecasts of international air travel demand. However, the forecast by Boeing and Airbus focuses more on the aircraft fleet mix than on passenger enplanements for the future years. On the other hand, FAA publishes the forecast of international enplanements for four different world areas: Canada, Atlantic, Asia Pacific, and Latin America. The FAA forecast of enplanements to each world area and the passenger enplanements predicted by the models developed are compared in Table 15. The average growth rates for Canada and Latin America areas forecasted by our modes are close to FAA forecasts. Disparities are found between the predictions for the other two world areas, which may be explained by the assumptions made by the FAA on values of GDP used.

It should be noted that GDP data used in FAA forecast is different from the GDP forecast employed in this analysis. The FAA uses INS Form I-92 International Air Travel Statistics published by the U.S. Department of Commerce as the data source to collect the passenger enplanement flows from the U.S. to the rest of the world. Our study uses T-100 international segment data collected by the U.S. Department of Transportation as the main data source of the dependent variables. The disparities observed between the FAA predictions and our models can be explained by the different sources of data sets used.



Source: Historical (1990-2004) Data: U.S. DOT BTS T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 25. Historical and Forecast Passenger Enplanements from the U.S. to each World Area.

Table 15. Model Forecast Results. vs. FAA Forecast of International Enplanements.

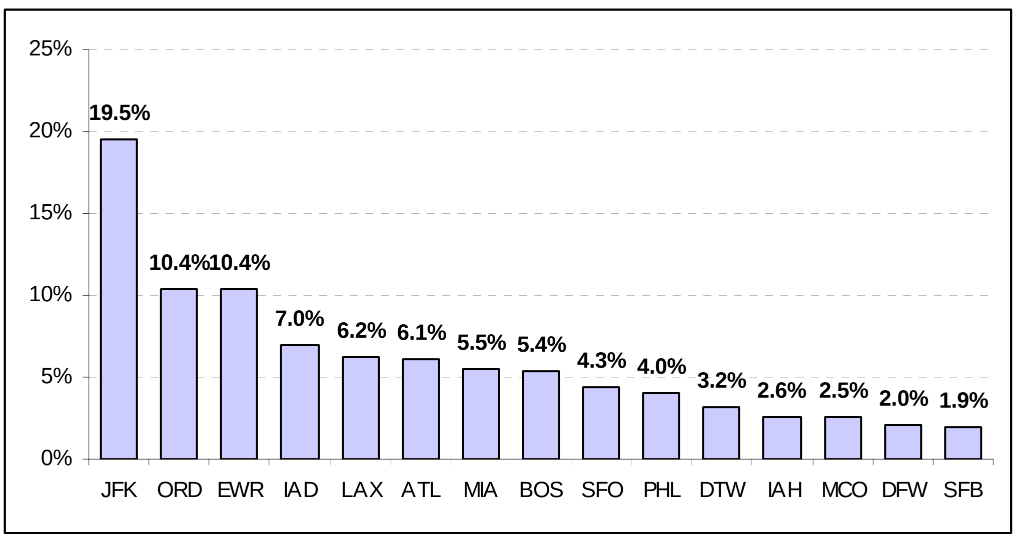
Year	Atlantic (Europe + Middle East + Africa)		Canada		Asia-Pacific (Asia + Oceania)		Latin America (South America + Caribbean & Central America + Mexico)		Total	
	VT ASTL	FAA	VT ASTL	FAA	VT ASTL	FAA	VT ASTL	FAA	VT ASTL	FAA
Historical:										
1990	29,205,746	-	13,372,442	-	16,203,384	-	25,583,964	-	84,365,536	-
1991	26,819,108	-	12,208,898	-	16,029,698	-	26,581,334	-	81,639,038	-
1992	30,894,972	-	12,909,256	-	17,692,400	-	28,102,618	-	89,599,246	-
1993	32,451,184	-	13,027,898	-	18,178,708	-	30,213,780	-	93,871,570	-
1994	33,965,486	-	12,830,128	-	19,977,886	-	31,319,582	-	98,093,082	-
1995	35,916,456	-	13,965,096	-	22,400,820	-	32,885,492	-	105,167,864	-
1996	38,786,178	-	15,380,538	-	24,202,444	-	34,646,116	-	113,015,276	-
1997	42,096,134	-	16,145,862	-	25,102,928	-	36,984,330	-	120,329,254	-
1998	45,668,304	46,567,306	16,879,776	19,010,291	23,215,008	22,918,958	39,369,768	37,651,295	125,132,856	126,147,850
1999	49,399,702	48,742,997	17,298,564	19,644,170	24,255,722	24,256,285	41,926,084	38,802,278	132,880,072	131,445,730
2000	53,781,136	53,043,272	18,152,852	20,824,399	26,445,622	25,961,783	44,684,024	40,800,235	143,063,634	140,629,689
2001	47,750,922	47,490,264	17,075,400	18,567,599	23,543,158	22,990,055	41,907,912	38,807,296	130,277,392	127,855,214
2002	44,609,666	43,414,919	16,961,652	17,574,815	23,000,858	22,251,997	40,635,994	36,866,017	125,208,170	120,107,748
2003	44,879,124	43,796,779	17,052,424	16,883,063	20,551,374	19,997,446	43,198,756	38,716,715	125,681,678	119,394,003
2004	49,717,422	48,736,873	19,258,480	18,491,573	24,421,016	23,855,777	47,559,360	42,405,432	140,956,278	133,489,655
Forecast:										
2005*	51,878,852	49,795,806	20,006,168	19,907,843	25,939,938	24,638,861	50,272,398	44,356,082	148,097,356	138,698,591
2006*	54,661,878	52,720,001	20,752,172	20,962,958	27,507,464	26,382,573	52,900,548	46,662,545	155,822,062	146,728,078
2007*	58,126,798	56,378,487	21,520,570	21,791,256	29,127,752	28,949,649	55,419,734	49,187,206	164,194,854	156,306,597
2008*	61,546,656	59,500,437	22,312,006	22,637,054	30,818,398	31,458,309	58,115,304	51,810,415	172,792,364	165,406,215
2009*	64,889,222	62,281,726	23,127,214	23,475,019	32,582,378	33,937,871	61,086,728	54,510,736	181,685,542	174,205,352
2010*	68,285,194	64,872,155	23,966,836	24,334,290	34,419,392	36,424,124	64,212,350	57,285,661	190,883,772	182,916,230
2011*	71,707,108	67,370,871	24,831,668	25,221,984	36,333,700	38,947,241	67,437,456	60,140,679	200,309,932	191,680,776
2012*	75,092,302	69,821,762	25,722,442	26,116,355	38,342,230	41,521,361	70,775,904	63,078,863	209,932,878	200,538,341
2013*	78,549,430	72,262,305	26,639,956	27,018,352	40,448,826	44,153,743	74,225,578	66,099,835	219,863,790	209,534,235
2014*	82,015,864	74,717,717	27,584,974	27,941,010	42,660,854	46,859,193	77,783,878	69,214,330	230,045,570	218,732,251
2015*	85,512,626	77,207,391	28,558,352	28,889,564	44,985,032	49,647,136	81,458,520	72,427,555	240,514,530	228,171,646
2016*	89,089,910	79,742,115	29,560,918	29,866,903	47,430,096	52,525,528	85,276,110	75,746,482	251,357,034	237,881,028
2017*	92,744,468	82,332,448	30,593,588	30,869,731	49,971,270	55,497,863	89,233,154	79,172,889	262,542,480	247,872,930
Average Annual Growth:										
2005-2017	**5.0%**	**4.3%**	**3.6%**	**3.7%**	**5.6%**	**7.0%**	**4.9%**	**4.9%**	**4.9%**	**5.0%**

Source: FAA: FAA Aerospace Forecasts Fiscal Year 2006-2017.

VT ASTL: Historical (1990-2004) Data: U.S. DOT BTS T-100 International Segment Data, http://www.transtats.bts.gov/.

4.2 Results from Airport Market Share Analysis

As discussed in Chapter 3, the airport market share is more correlated with the airline's business share than the level of service at the airport. For example, the market share to Europe from JFK airport is found to decrease from 38% in 1990 to 19% in 2004 primarily because two main airlines (Pan America Airways and Trans World Airways) declared bankruptcy over the period of time. During the same period, the market share to Europe of EWR increased from 5% to 10% because Continental Air Lines increased their business share at this airport. This implies that an airline business model that explains the evolution of the airline business might be needed in order to forecast the airport market share of a region where airports compete for the same passengers. In our analysis, it is assumed that the market share of each airport to each World Region in year 2004 remains constant over the whole forecast period from 2005 to 2030.



Source: U.S. DOT BTS, T-100 International Segment Data, http://www.transtats.bts.gov/.

Figure 26. Assumed Market Share of Top Fifteen Airports to Europe.

The assumed market share of the top fifteen airports to each World Region is presented in Table 16. The top fifteen U.S. airports to Europe and their assumed market share are also graphically illustrated in Figure 26. The figures for the other World

Regions are attached in Appendix D. In the year 2004, for example, more than half of the total air passengers from the U.S. to Europe departed from JFK, ORD, EWR, IAD or LAX airports. This pattern is assumed to be same in the future in the model developed.

Table 16. Assumed Market Share by World Region (Top 15 Airports).

Airport Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Africa	JFK	ATL	BOS	IAH	BWI	-	-	-	-	-	-	-	-	-	-
	59.1%	31.3%	4.4%	3.1%	2.0%	-	-	-	-	-	-	-	-	-	-
Asia	LAX	SFO	JFK	ORD	DTW	SEA	EWR	DFW	MSP	ATL	IAD	IAH	SJC	PDX	LAS
	21.7%	15.3%	6.2%	6.2%	4.5%	3.2%	1.5%	1.4%	1.4%	1.3%	1.1%	0.8%	0.6%	0.4%	0.0%
Canada	ORD	LAX	MSP	LGA	SFO	EWR	SEA	DTW	LAS	ATL	DFW	DEN	BOS	MIA	IAH
	10.9%	8.5%	5.9%	5.7%	5.3%	5.0%	4.9%	3.7%	3.4%	3.2%	3.2%	3.2%	3.2%	3.0%	2.6%
Caribbean & Central America	MIA	JFK	ATL	EWR	IAH	PHL	FLL	LAX	CLT	BOS	DFW	MCO	ORD	IAD	BWI
	28.5%	14.5%	6.3%	5.5%	5.4%	4.3%	4.1%	3.9%	3.8%	2.1%	1.6%	1.3%	1.2%	1.2%	1.1%
Europe	JFK	ORD	EWR	IAD	LAX	ATL	MIA	BOS	SFO	PHL	DTW	IAH	MCO	DFW	SFB
	19.5%	10.4%	10.4%	7.0%	6.2%	6.1%	5.5%	5.4%	4.3%	4.0%	3.2%	2.6%	2.5%	2.0%	1.9%
Mexico	LAX	IAH	DFW	ORD	MIA	ATL	PHX	SFO	JFK	DEN	EWR	CLT	LAS	OAK	MSP
	17.2%	14.5%	11.0%	7.2%	5.6%	4.8%	4.6%	2.9%	2.8%	2.5%	2.5%	2.2%	2.0%	1.8%	1.7%
Middle East	JFK	EWR	ORD	DTW	LAS	CLE	-	-	-	-	-	-	-	-	-
	59.5%	31.9%	7.1%	1.4%	0.0%	0.0%	-	-	-	-	-	-	-	-	-
Oceania	LAX	SFO	-	-	-	-	-	-	-	-	-	-	-	-	-
	71.3%	7.7%	-	-	-	-	-	-	-	-	-	-	-	-	-
South America	MIA	JFK	ATL	IAH	DFW	EWR	LAX	IAD	FLL	ORD	PHL	RDU	MCO	-	-
	54.5%	13.6%	7.1%	5.5%	5.2%	3.7%	3.5%	2.9%	1.7%	1.6%	0.0%	0.0%	0.0%	-	-
U.S. Int.	JFK	LAX	EWR	SFO	SEA	LAS	IAH	ORD	IAD	MIA	MCO	FLL	RSW	PIE	SFB
	22.5%	17.5%	9.5%	9.0%	7.3%	3.3%	3.1%	2.6%	2.2%	2.2%	1.6%	1.0%	1.0%	0.9%	0.3%

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

4.3 Average Seats per Aircraft and Load Factor analysis

The average seats per aircraft and load factor for each airport to each region are shown in Tables 17 and 18, respectively. Per our discussion in Chapter 3 (see Figure 19), the average seats per aircraft for each region are expected to remain relatively constant (except for Canada) in the last two years. The load factor shows increasing trends across all the regions. From both the average aircraft size and load factor are assumed to be constant after the year 2004. The average aircraft size and the load factor are adjustable in the TSAM model, as will be explained later in this chapter.

4.4 Forecast Results of Total International Operations at Airports in the U.S.

The forecasts of total international flight operations at the top 66 airports are presented in Tables 19 and 20. The total international flight operations at airports in the U.S. are expected to increase from 1.2 million to 3.4 million during the period from 2005 to 2030. This represents a 4.2 percent annual growth. The growth rate of international flight operations is forecast to change unevenly by airport.

The total international flight operations at each airport for year 2004 (historical) and forecast years 2010, 2020 and 2030 are presented in Figures 27 through 30, respectively. For most of the airports a 4 percent annual growth is observed. It should be reminded that the forecast is based on the assumption that the facility capacity at each airport will not constrain the international flight operations.

Table 17. Assumed Average Seats Per Aircraft by World Region (Top 15 Airports).

Airport Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Africa	JFK	ATL	BOS	IAH	BWI	-	-	-	-	-	-	-	-	-	-
	278.6	336.6	235.5	211.3	288.8	-	-	-	-	-	-	-	-	-	-
Asia	LAX	SFO	JFK	ORD	DTW	SEA	EWR	DFW	MSP	ATL	IAD	IAH	SJC	PDX	LAS
	340.1	315.4	305.8	292.2	402.2	299.6	260.1	237.3	402.9	293.9	276.6	283.0	221.9	255.1	364.7
Canada	ORD	LAX	MSP	LGA	SFO	EWR	SEA	DTW	LAS	ATL	DFW	DEN	BOS	MIA	IAH
	98.2	136.4	95.3	87.0	132.4	73.1	51.9	68.2	143.3	65.3	118.0	93.7	55.9	141.3	89.2
Caribbean & Central America	MIA	JFK	ATL	EWR	IAH	PHL	FLL	LAX	CLT	BOS	DFW	MCO	ORD	IAD	BWI
	127.4	199.8	154.6	144.4	146.2	146.5	47.5	150.7	143.8	174.1	153.9	76.2	164.5	154.7	155.5
Europe	JFK	ORD	EWR	IAD	LAX	ATL	MIA	BOS	SFO	PHL	DTW	IAH	MCO	DFW	SFB
	256.5	242.3	230.0	253.9	310.9	222.5	302.3	251.5	314.6	233.5	279.5	267.9	368.5	224.5	375.9
Mexico	LAX	IAH	DFW	ORD	MIA	ATL	PHX	SFO	JFK	DEN	EWR	CLT	LAS	OAK	MSP
	179.0	152.8	145.9	138.1	138.6	128.6	161.4	142.2	141.3	156.7	159.4	87.3	150.3	128.9	161.7
Middle East	JFK	EWR	ORD	DTW	LAS	CLE	-	-	-	-	-	-	-	-	-
	304.1	298.7	257.8	240.4	16.0	16.0	-	-	-	-	-	-	-	-	-
Oceania	LAX	SFO	-	-	-	-	-	-	-	-	-	-	-	-	-
	358.6	354.7	-	-	-	-	-	-	-	-	-	-	-	-	-
South America	MIA	JFK	ATL	IAH	DFW	EWR	LAX	IAD	FLL	ORD	PHL	RDU	MCO	-	-
	196.7	222.8	200.7	155.8	189.6	167.6	250.2	193.0	162.6	193.4	188.0	172.0	178.0	-	-
U.S. Int.	JFK	LAX	EWR	SFO	SEA	LAS	IAH	ORD	IAD	MIA	MCO	FLL	RSW	PIE	SFB
	317.9	392.9	301.2	363.9	300.3	387.5	231.9	243.2	274.8	325.6	179.0	173.6	280.4	166.3	247.4

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Table 18. Assumed Load Factor by World Region (Top 15 Airports).

Airport Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Africa	JFK	ATL	BOS	IAH	BWI	-	-	-	-	-	-	-	-	-	-
	72.4%	77.7%	64.7%	29.4%	53.9%	-	-	-	-	-	-	-	-	-	-
Asia	LAX	SFO	JFK	ORD	DTW	SEA	EWR	DFW	MSP	ATL	IAD	IAH	SJC	PDX	LAS
	75.4%	80.0%	77.7%	80.2%	87.5%	84.6%	75.5%	79.5%	89.2%	77.2%	76.1%	80.4%	77.5%	76.9%	27.4%
Canada	ORD	LAX	MSP	LGA	SFO	EWR	SEA	DTW	LAS	ATL	DFW	DEN	BOS	MIA	IAH
	63.4%	71.6%	64.7%	62.0%	71.9%	62.8%	64.9%	59.0%	73.1%	69.1%	64.5%	70.6%	59.8%	73.5%	60.7%
Caribbean & Central America	MIA	JFK	ATL	EWR	IAH	PHL	FLL	LAX	CLT	BOS	DFW	MCO	ORD	IAD	BWI
	62.6%	67.8%	72.0%	72.2%	68.1%	69.1%	59.8%	77.9%	69.4%	61.9%	68.7%	63.4%	72.9%	72.6%	72.6%
Europe	JFK	ORD	EWR	IAD	LAX	ATL	MIA	BOS	SFO	PHL	DTW	IAH	MCO	DFW	SFB
	80.0%	80.3%	80.8%	79.5%	84.4%	81.4%	84.5%	82.3%	84.1%	80.2%	83.3%	71.1%	85.3%	77.8%	89.8%
Mexico	LAX	IAH	DFW	ORD	MIA	ATL	PHX	SFO	JFK	DEN	EWR	CLT	LAS	OAK	MSP
	74.9%	73.4%	77.7%	77.4%	71.9%	73.1%	54.6%	64.8%	75.7%	78.7%	78.3%	74.0%	67.2%	71.1%	83.4%
Middle East	JFK	EWR	ORD	DTW	LAS	CLE	-	-	-	-	-	-	-	-	-
	77.4%	81.1%	64.3%	45.6%	62.5%	43.8%	-	-	-	-	-	-	-	-	-
Oceania	LAX	SFO	-	-	-	-	-	-	-	-	-	-	-	-	-
	72.2%	78.9%	-	-	-	-	-	-	-	-	-	-	-	-	-
South America	MIA	JFK	ATL	IAH	DFW	EWR	LAX	IAD	FLL	ORD	PHL	RDU	MCO	-	-
	67.5%	74.2%	71.9%	70.5%	62.8%	72.1%	84.2%	79.3%	62.1%	76.0%	82.4%	80.2%	61.2%	-	-
U.S. Int.	JFK	LAX	EWR	SFO	SEA	LAS	IAH	ORD	IAD	MIA	MCO	FLL	RSW	PIE	SFB
	55.0%	73.9%	39.5%	84.1%	44.1%	43.1%	25.4%	19.7%	25.2%	35.4%	37.1%	35.8%	50.0%	34.7%	80.6%

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Table 19. Forecast International Passenger Flight Operations at 66 U.S. Airports.

Rank	Airport	2004	2010	2015	2020	2025	2030	Annual Growth Rate 2004-2030
Total (66 airports)		**1,172,908**	**1,518,776**	**1,916,245**	**2,348,694**	**2,855,333**	**3,449,581**	**4.2%**
1	MIA	136,800	175,580	233,710	291,460	359,980	441,290	4.6%
2	JFK	98,086	134,350	169,690	209,950	256,510	310,480	4.5%
3	LAX	95,602	127,270	159,500	198,000	243,770	298,240	4.5%
4	ORD	80,892	102,060	132,080	161,230	195,050	236,310	4.2%
5	IAH	74,260	99,853	125,760	156,430	192,900	234,360	4.5%
6	EWR	70,342	93,373	115,920	141,670	171,460	205,970	4.2%
7	ATL	57,016	75,870	94,458	115,820	140,650	169,560	4.3%
8	DFW	43,562	59,057	74,605	92,997	114,840	140,790	4.6%
9	SFO	38,602	49,609	65,690	81,935	101,150	123,920	4.6%
10	FLL	37,774	47,410	57,865	70,163	84,734	102,000	3.9%
11	BOS	36,572	47,103	57,309	68,826	81,995	97,063	3.8%
12	PHL	36,246	44,532	56,559	68,099	81,413	96,789	3.8%
13	SEA	34,860	44,076	54,552	66,346	79,825	95,245	3.9%
14	IAD	33,200	42,691	53,799	64,758	77,522	92,401	4.0%
15	DTW	30,154	39,149	47,984	58,219	70,108	83,940	4.0%
16	MSP	25,060	30,716	38,718	46,536	55,610	66,147	3.8%
17	LGA	22,440	27,909	33,315	39,592	46,887	55,366	3.5%
18	CLT	17,838	22,777	28,374	34,982	42,841	52,198	4.2%
19	PHX	17,298	21,806	27,900	33,882	40,921	49,210	4.1%
20	DEN	15,026	19,359	23,636	28,628	34,472	41,323	4.0%
21	MCO	14,394	18,421	22,503	27,167	32,571	38,836	3.9%
22	CVG	14,336	18,283	22,124	26,499	31,525	37,308	3.7%
23	LAS	11,588	15,042	18,477	22,514	27,272	32,885	4.1%
24	DCA	8,814	10,960	13,088	15,559	18,432	21,773	3.5%
25	PIT	8,166	9,926	12,410	14,820	17,611	20,837	3.7%
26	CLE	7,744	9,730	11,688	13,958	16,630	19,920	3.7%
27	PBI	7,642	9,458	11,534	13,900	16,611	19,782	3.7%
28	BWI	7,366	9,083	11,459	13,818	16,599	19,674	3.9%
29	PDX	7,314	8,941	11,245	13,513	16,150	19,221	3.8%
30	LKE	6,002	7,469	8,900	10,559	12,482	14,712	3.5%
31	SLC	5,670	6,867	8,562	10,235	12,188	14,464	3.7%
32	BDL	4,948	6,167	7,365	8,758	10,374	12,509	3.6%
33	MKE	4,078	4,944	6,434	8,096	10,098	12,253	4.3%
34	SFB	3,796	4,816	6,246	7,565	9,049	10,721	4.1%
35	ALB	3,734	4,808	6,187	7,417	8,857	10,543	4.1%

Source: 2004 historical data: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Table 20. Forecast International Passenger Flight Operations at 66 U.S. Airports (Continued).

Rank	Airport	2004	2010	2015	2020	2025	2030	Annual Growth Rate 2004-2030
36	SAT	3,706	4,647	5,538	6,570	7,767	9,320	3.6%
37	MEM	3,312	4,113	5,284	6,424	7,759	9,156	4.0%
38	RDU	3,142	3,833	4,814	5,892	7,342	9,090	4.2%
39	TPA	2,924	3,541	4,686	5,753	6,832	8,074	4.0%
40	STL	2,812	3,504	4,461	5,440	6,601	7,979	4.1%
41	OAK	2,704	3,480	4,460	5,351	6,384	7,892	4.2%
42	CMH	2,496	3,118	3,922	5,004	6,312	7,580	4.4%
43	HPN	2,306	3,049	3,861	4,835	6,010	7,420	4.6%
44	MDW	2,260	2,880	3,729	4,437	5,262	6,386	4.1%
45	SJC	2,182	2,871	3,422	4,133	5,154	6,221	4.1%
46	IND	2,002	2,537	3,284	4,060	4,802	5,659	4.1%
47	MHT	1,948	2,454	3,070	3,696	4,429	5,290	3.9%
48	SAN	1,892	2,339	2,890	3,429	4,053	4,943	3.8%
49	MDT	1,720	2,140	2,552	3,200	3,991	4,778	4.0%
50	PVD	1,684	2,068	2,543	3,027	3,771	4,672	4.0%
51	ABE	1,662	2,024	2,505	3,023	3,579	4,219	3.6%
52	ONT	1,468	1,902	2,465	2,976	3,523	4,158	4.1%
53	TUS	1,384	1,796	2,403	2,924	3,457	4,075	4.2%
54	BFI	1,370	1,706	2,061	2,480	2,974	3,555	3.7%
55	MSY	1,354	1,638	2,033	2,412	2,853	3,362	3.6%
56	ROC	1,258	1,511	1,866	2,213	2,616	3,084	3.5%
57	BNA	1,100	1,388	1,673	2,006	2,395	2,851	3.7%
58	MCI	1,044	1,331	1,617	1,953	2,346	2,810	3.9%
59	RSW	1,018	1,260	1,598	1,919	2,287	2,709	3.8%
60	PIE	1,014	1,241	1,564	1,880	2,249	2,677	3.8%
61	DAB	926	1,145	1,389	1,676	2,016	2,419	3.8%
62	MLB	904	1,074	1,356	1,636	1,968	2,362	3.8%
63	ELP	638	870	1,108	1,394	1,739	2,155	4.8%
64	SMF	598	773	1,035	1,302	1,625	2,013	4.8%
65	MFE	484	628	840	1,058	1,319	1,635	4.8%
66	MYR	370	440	555	670	806	967	3.8%

Source: 2004 historical data: U.S. DOT BTS, T-100 International Segment Data in 2004,
http://www.transtats.bts.gov/.

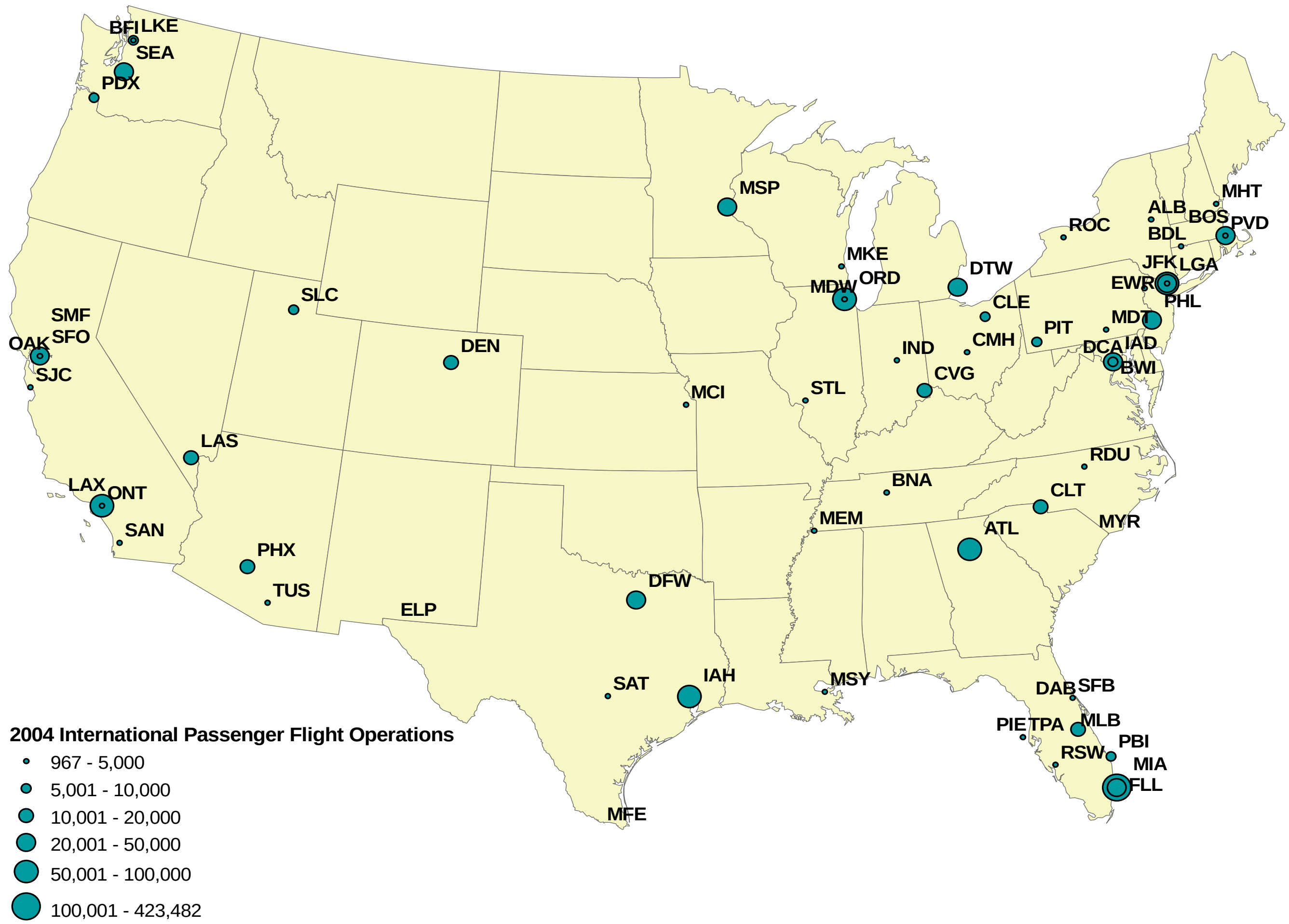


Figure 27. International Air Passenger Flight Operations by Airport (Year 2004 Historical Data).

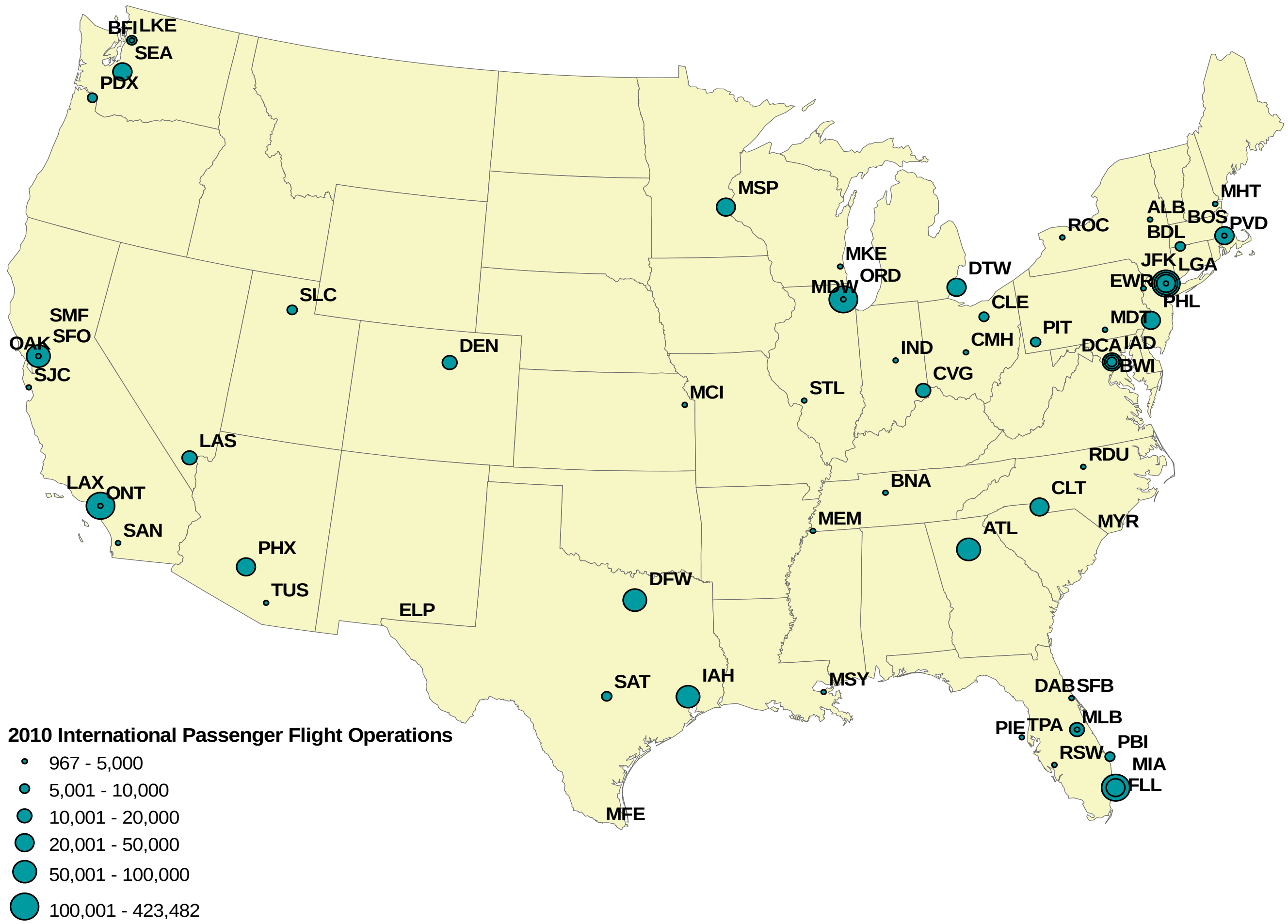


Figure 28. 2010 Forecast International Air Passenger Flight Operations by Airport.

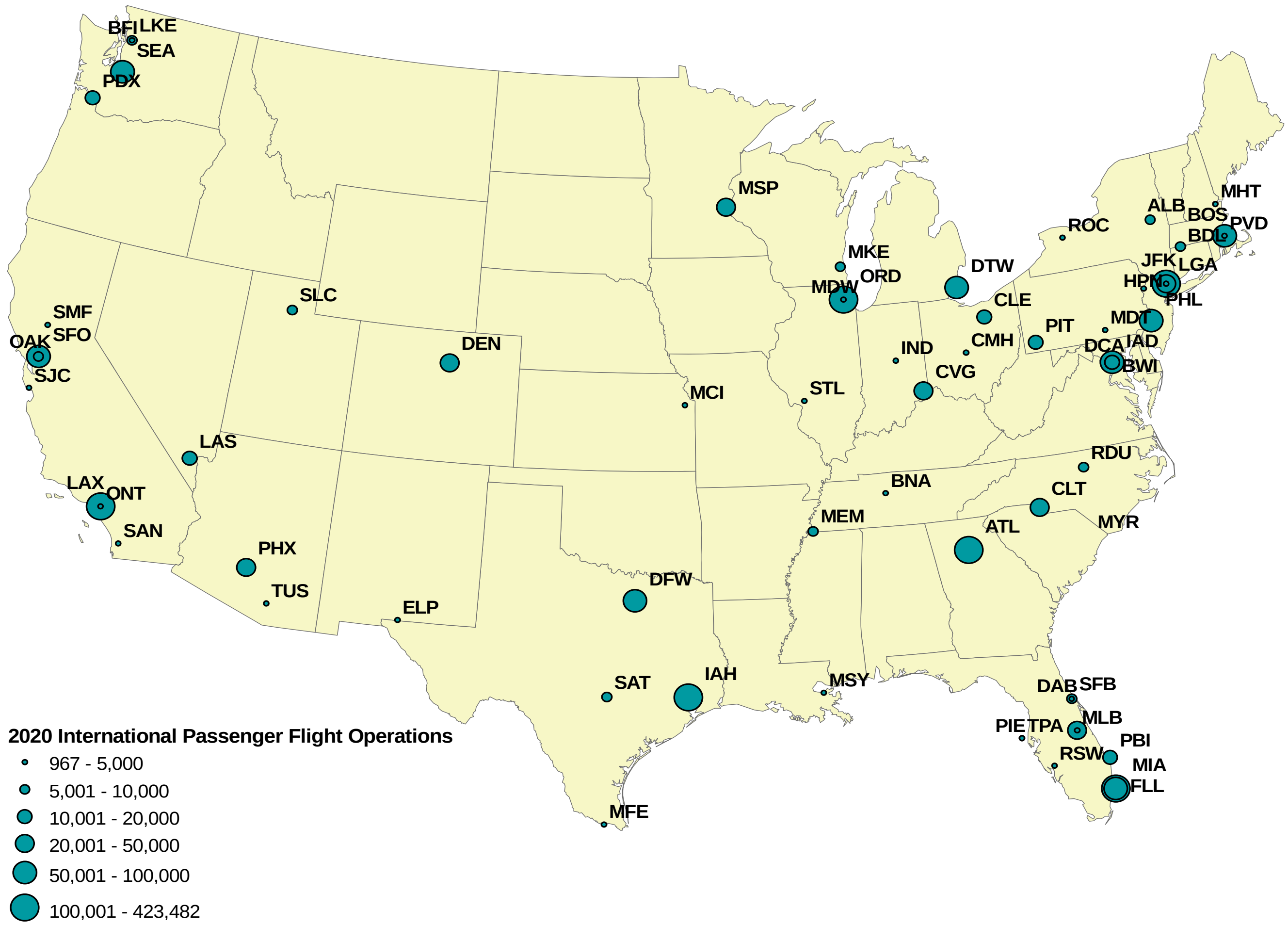


Figure 29. 2020 Forecast International Air Passenger Flight Operations by Airport.

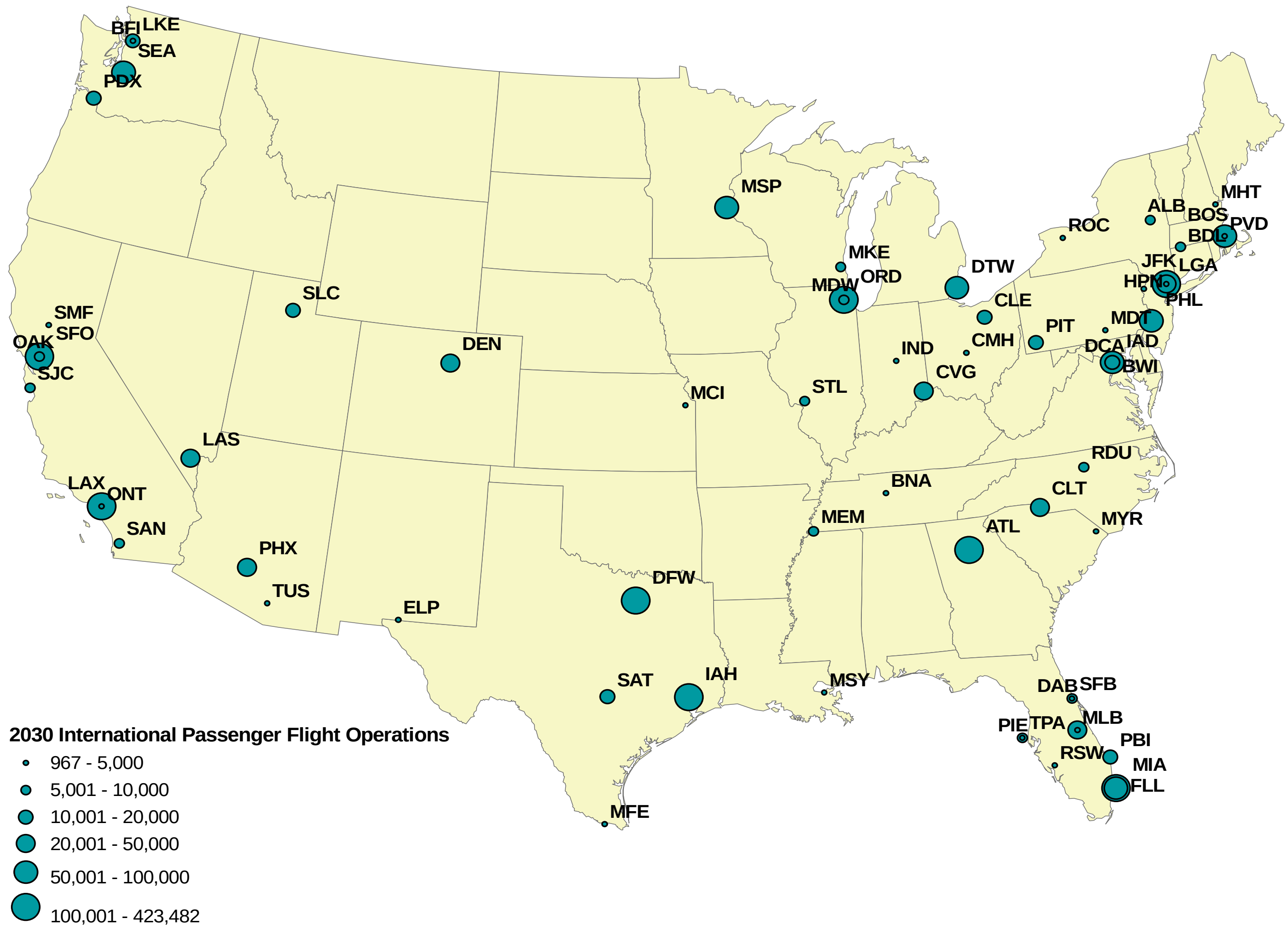


Figure 30. 2030 Forecast International Passenger Flight Operations by Airport.

4.5 Model Application

Combining the projections of domestic flight operations, with the forecasts of international flight operations between the U.S. and the rest of the world, we can plan airport facility requirements in the future. The forecasts of international flight operations also can be used for policy making, airport planning, marketing and investment decision making analysis. For example, the combined effect of domestic and international flight operations and other aviation activity at an airport can be used to predict capacity and delay analyses. This information can be used by an airport authority to evaluate the impacts of current and future planning decisions.

The model described in this analysis has been integrated into the Transportation Systems Analysis Model (TSAM) [24] developed by the Air Transportation Systems Laboratory at Virginia Tech. TSAM predicts domestic origin-destination passenger flows between 3091 counties in the U.S. It also predicts origin-destination passenger flows between airports. The framework of TSAM is depicted in Figure 31.

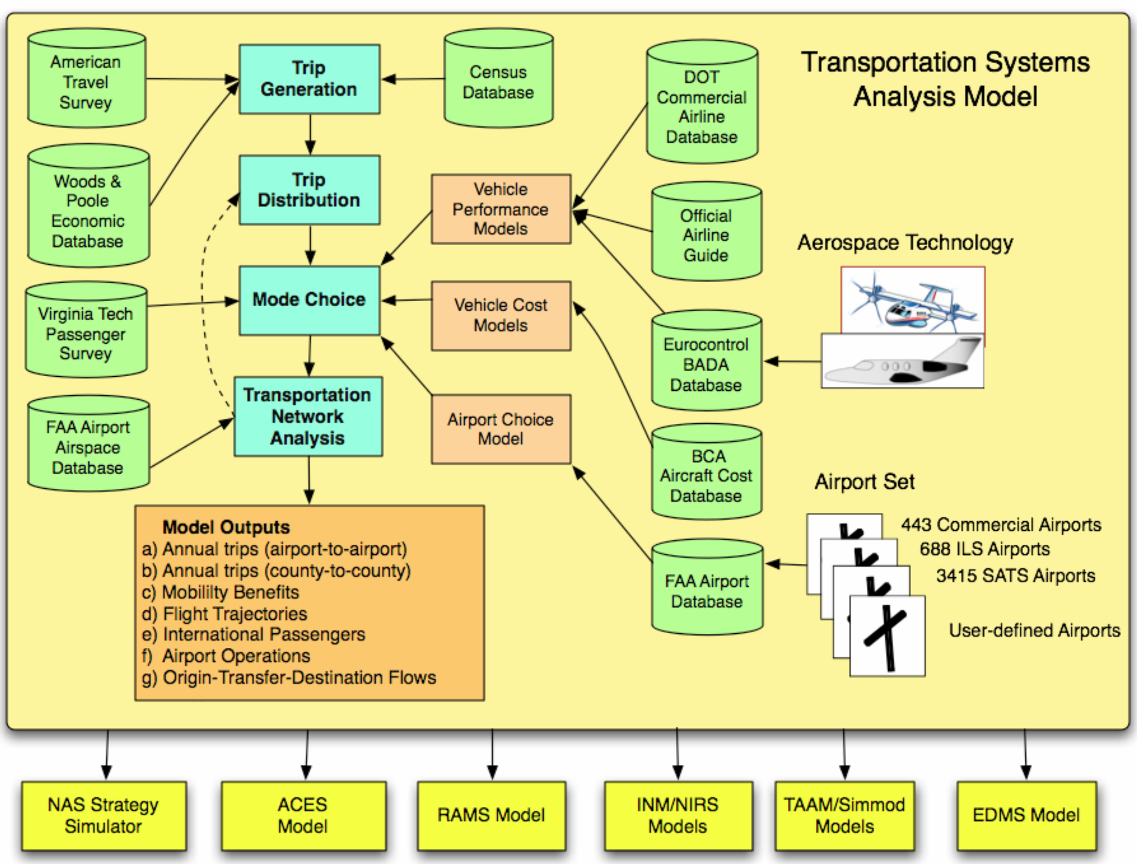


Figure 31. Framework of Transportation System Analysis Model (TSAM).

TSAM was originally calibrated to predict domestic passengers. However, large metropolitan airports (large hub airports) have significant international passenger flows. The modeling effort described in this analysis focuses on estimating international passenger flows to and from 66 airports in the U.S. that handled 99.8% of total international flight operations in the U.S. in year 2004. This analysis addresses a critical gap in the TSAM model.

Figures 32 and 33 show two sample screens implemented in TSAM to portray nationwide international enplanement demands and airport-level international passenger flight operation demands, respectively. In Figure 32, the international enplanement demands at 66 airports in year 2030 are presented. Following standard nomenclature in TSAM, larger diameter circles denote higher international enplanements demands at airports. Moreover, color-coding is also used to distinguish between the relative magnitudes of the demands at each airport.

Figure 33 illustrates the international passenger enplanements demand forecast at Atlanta International Airport (ATL). The graph shows the expected growth in enplanements demand over time. Each World Region is represented in the figure using a color-coding scheme. As described, ten World Regions are modeled and presented in the TSAM model as airport-level projections.

It should be pointed out that there exists uncertainty in the future values of the input variables. For example, load factor and average aircraft size are assumed to be unchanged in the forecast. The collected GDP projections for each World Region are also assumed to be correct for the future. However, it is almost impossible to forecast future values of aircraft size and load factor. Considering this uncertainty, the model can be used to predict scenarios that provide a range of the forecast instead of a single prediction value.

For the scenario analysis, a graphical user interface (GUI) is implemented in TSAM as shown in Figure 34. Using the GUI, users can easily change the scaling factors to adjust the input values of GDP, load factor and average seats per aircraft in future years. Therefore, the sensitivity of both international passenger enplanements and flight operations to different assumed parameters can be easily evaluated in the enhanced TSAM model.

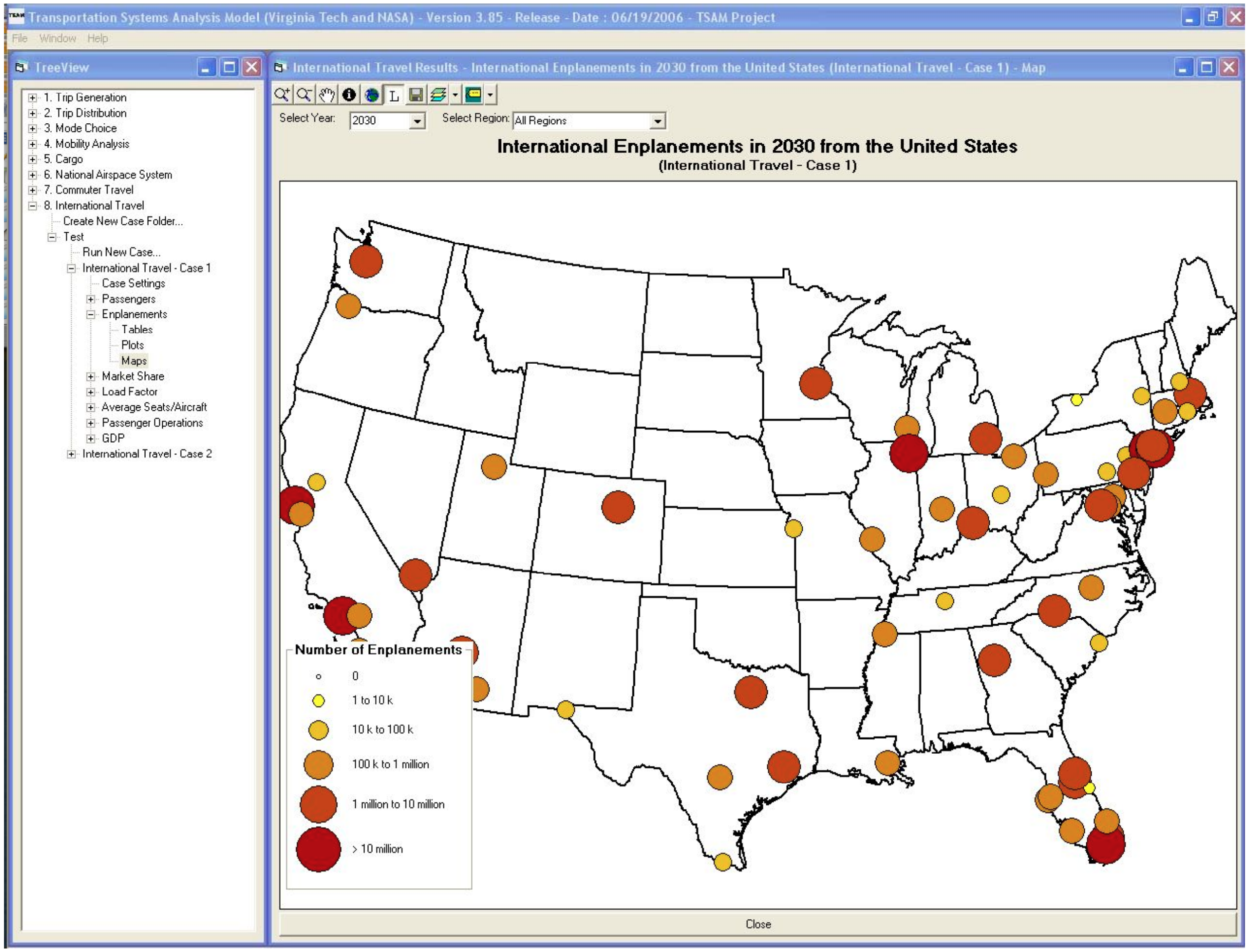


Figure 32. TSAM International Enplanements Map.

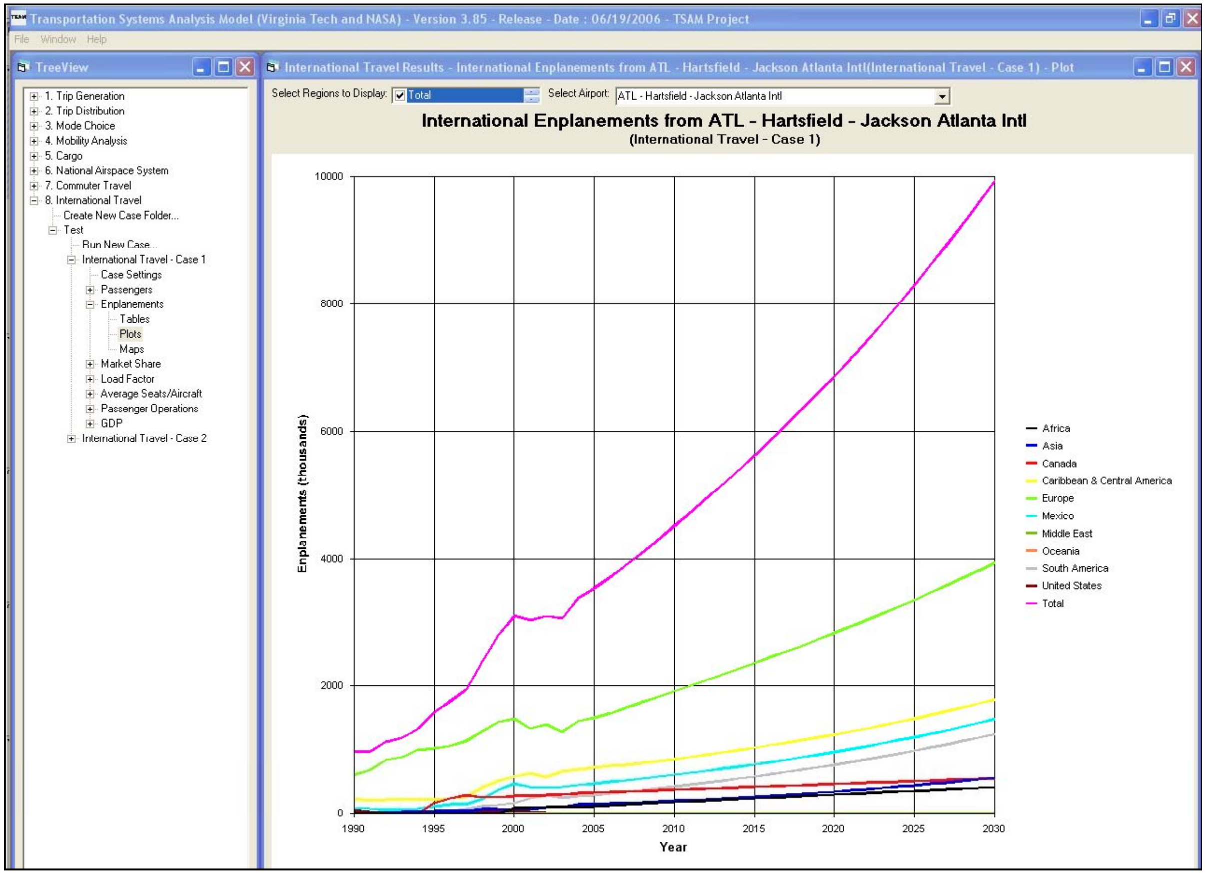


Figure 33. TSAM International Enplanements Profile at Atlanta Hartsfield International Airport.

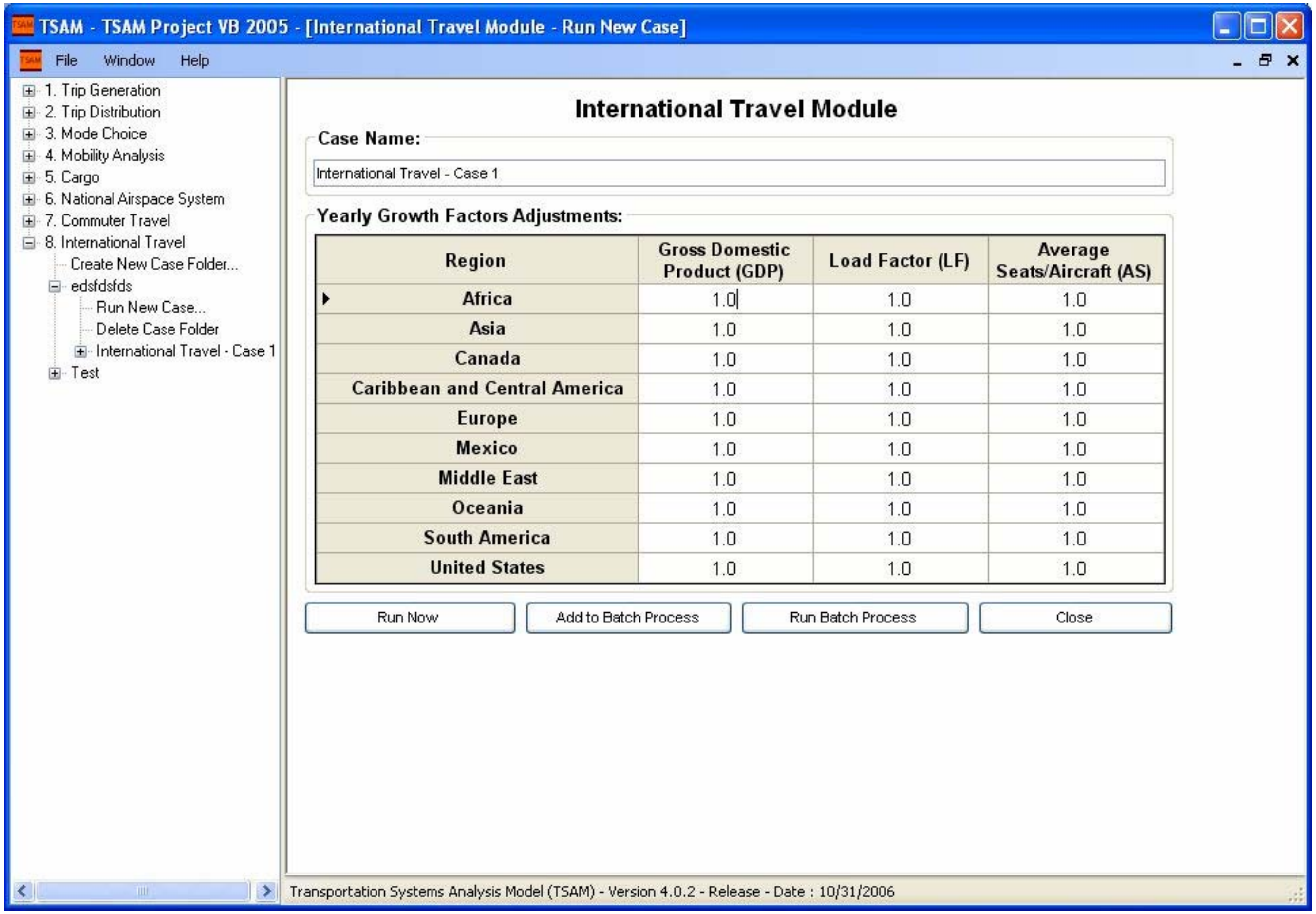


Figure 34. TSAM User Interface to Adjust the Input Values of GDP, Load Factor and Average Seats/Aircraft.

Chapter 5 Conclusions and Recommendations

5.1 Conclusion

The objective of this analysis was to develop a model to forecast annual international flight operations at sixty-six U.S. airports. In the forecast, a “top-down” methodology is applied in three steps. In the first step, individual linear regression models are developed to forecast the total annual international passenger enplanements from the U.S. to each of nine World Regions. The forecasted nation-wide passenger enplanements are then distributed among international airports in the U.S. using market share assumptions for each airport. In the final step, the international passenger enplanements at each airport are converted to flight operations. In the conversion process, average load factor and average seats per aircraft are used.

All the regression models developed are statistically valid and have parameters that are sensible both in terms of signs (conform to economic theory) and in terms of magnitude (i.e., they seem reasonable from a practical perspective). World Region GDP is used as the main explanatory variable along with a dummy variable reflecting the impact of Sep. 11, 2001 terrorist attack on the future international passenger enplanements demand in the U.S.

The airport market share analysis concludes that the airline business is a crucial factor to explain the changes associated with airport market share.

The model presented has been integrated into the Transportation System Analysis Model (TSAM). TSAM is a comprehensive intercity transportation planning tool. The international flight operations and their future forecasts can be presented both spatially and graphically using TSAM geographic information-based interface. Tables summarizing the international traffic at each airport (both operations and enplanements) are also part of the model solution presented in TSAM.

Through a simple graphic user interface implemented in the TSAM model, the user can test different future scenarios by defining a series of scaling factors for GDP, load factor and average seats per aircraft. The default values for the latter two variables are predefined in the model using 2004 historical data derived from Department of Transportation T100 international segment data.

5.2 Recommendations

To enhance the models presented in this analysis, the following issues need to be addressed in the future:

1. To account for the impacts of practical airport capacity, an airport capacity constraint should be considered in future forecasts of international air passenger demand. In this study, it is assumed that the additional airport capacity required to satisfy the predicted future air passenger demand is always available. A forecast without any airport capacity constraints is likely to yield higher demand than the actual demand expected in the future when the demand at an airport approaches the capacity.
2. Besides GDP, other variables should be investigated that might increase the R^2_{adj} value of the regression models for several World Regions such as Asia, Oceania and Africa. Globalization, international trade, declining fares and network development can all be used to explain additional air travel demand in the future.
3. Load factors and average seats per aircraft in the future are important parameters in the model developed. In this study, both are assumed to be constant in the future years. However, operational factors and airline scheduling practices would change when the demand at an airport is near capacity. For example, the airlines may use larger aircraft with increasing congestion and delays in the future [26]. Therefore, more analysis is recommended to find better causality between load factors and average seats per aircraft as a function of airport excess capacity and airline strategies.
4. Establishing new hubs is another airline strategy to respond to the congestion at existing airports [26], which will influence the future airport market share structure in the U.S. The change is recommended to consider in airport market share analyses in the future.

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Appendix A: Sample of T100 International Segment data

Table A. Sample of T100 International Segment Data in Year 2004.

YEAR	QUARTER	MONTH	ORIGIN	ORIGIN_COUNTRY_NAME	ORIGIN_WAC	DEST	DEST_COUNTRY_NAME	DEST_WAC	SEATS	PASSENGERS	CARRIER_NAME	CLASS	DEPARTURES_PERFORMED
2004	1	3	MIA	United States of America	33	YYZ	Canada	936	1188	983	Air Canada	F	6
2004	1	1	BOS	United States of America	13	POP	Dominican Republic	5	1000	984	Icelandair	L	224
2004	1	2	MIA	United States of America	33	DUS	Germany	4	1298	984	Luftransport-Unternehmen	F	429
2004	1	1	DTW	United States of America	43	YUL	Canada	22	2750	985	Northwest Airlines Inc.	F	941
2004	1	2	LGA	United States of America	22	YUL	Canada	99	3663	986	Allegheny Airlines	F	941
2004	1	1	EWR	United States of America	21	WAW	Poland	5	1195	987	Polskie Linie Lotnicze	F	467
2004	1	2	MSP	United States of America	63	YQT	Canada	56	1904	989	Mesaba Airlines	F	936
2004	1	3	ORD	United States of America	41	GDL	Mexico	148	1200	973	Compania Mexicana De Aviaci	F	10
2004	1	3	JFK	United States of America	22	SDQ	Dominican Republic	224	1640	973	North American Airlines	F	8
2004	1	3	YYC	Canada	916	BNA	United States of America	1	74	44	Midwest Airlines Inc.	L	54
2004	1	3	CDG	France	427	MEM	United States of America	1	208	121	American Airlines Inc.	F	54
2004	1	1	YYZ	Canada	936	MEM	United States of America	23	0	0	Federal Express Corporation	G	54
2004	1	2	YYZ	Canada	936	MEM	United States of America	21	0	0	Federal Express Corporation	G	54
2004	1	1	YVR	Canada	906	BNA	United States of America	1	74	44	Midwest Airlines Inc.	L	54

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Appendix B: Countries Covered by each World Region

Table B. List of Countries by World Region.

U.S.

WAC	Description	WAC	Description
1	Alaska	51	Alabama
2	Hawaii	52	Kentucky
3	Puerto Rico	53	Mississippi
4	U.S. Virgin Islands	54	Tennessee
5	U.S. Pacific Trust Territories And Possessions	61	Iowa
11	Connecticut	62	Kansas
12	Maine	63	Minnesota
13	Massachusetts	64	Missouri
14	New Hampshire	65	Nebraska
15	Rhode Island	66	North Dakota
16	Vermont	67	South Dakota
21	New Jersey	71	Arkansas
22	New York	72	Louisiana
23	Pennsylvania	73	Oklahoma
31	Delaware	74	Texas
32	District of Columbia	81	Arizona
33	Florida	82	Colorado
34	Georgia	83	Idaho
35	Maryland	84	Montana
36	North Carolina	85	Nevada
37	South Carolina	86	New Mexico
38	Virginia	87	Utah
39	West Virginia	88	Wyoming
41	Illinois	91	California
42	Indiana	92	Oregon
43	Michigan	93	Washington
44	Ohio		
45	Wisconsin		

Mexico

WAC	Description
148	Mexico

Central America & Caribbean

WAC	Description	WAC	Description
106	Belize	233	Cayman Islands
110	Costa Rica	235	Guadeloupe-France
118	El Salvador	238	Haiti
127	Guatemala	243	Jamaica
131	Honduras	252	Martinique-France
153	Nicaragua	256	Montserrat

Table B. List of Countries by World Region *(Continued).*

Central America & Caribbean (Continued)

WAC	Description	WAC	Description
160	Panama Canal Zone	259	Netherlands Antilles
162	Panama Republic	273	Grenada and South Grenadines
202	Anguilla	275	St. Kitts and Nevis
204	Bahamas	276	St. Lucia
205	Barbados	277	Aruba
206	Antigua and Barbuda	279	St. Vincent and North Grenadines
207	Bermuda-UK	280	Trinidad and Tobago
219	Cuba	281	Turks and Caicos Islands-UK
221	Dominica	282	British Virgin Islands-UK
224	Dominican Republic		

South America

WAC	Description	WAC	Description
303	Argentina	344	French Guiana-France
312	Bolivia	350	Guyana
316	Brazil	365	Paraguay
324	Chile	368	Peru
327	Colombia	379	Surinam
337	Ecuador	385	Uruguay
340	Falkland Islands-UK	388	Venezuela

Europe

WAC	Description	WAC	Description
401	Albania	450	Italy
403	Austria	451	Latvia
407	Azerbaijan	452	Lithuania
409	Belgium	454	Luxembourg
410	Bosnia and Herzegovina	455	Macedonia
411	Bulgaria	456	Malta
413	Belarus	461	Netherlands
415	Croatia	465	Norway
417	Czechoslovakia	467	Poland
418	Czech Republic	469	Portugal
419	Denmark	473	Romania
422	Estonia	475	Russia (European)
425	Finland	477	Serbia and Montenegro
427	France	481	Slovenia
429	Germany	482	Spain
430	Berlin	483	Slovakia
431	Gibraltar-UK	484	Sweden
432	Georgia	486	Switzerland
433	Greece	488	Ukraine
437	Hungary	489	U.S.S.R. (European)
439	Iceland	493	United Kingdom
441	Ireland	497	Yugoslavia

Table B. List of Countries by World Region *(Continued).*

Africa

WAC	Description	WAC	Description
500	Algeria	543	Mali
502	Angola	548	Morocco
504	Cameroons	550	Mozambique
507	Cape Verde Islands	555	Nigeria
509	Central African Republic	562	Republic Of South Africa
510	Botswana	565	Zimbabwe
515	Congo	566	Rwanda
521	Equatorial Guinea	569	Senegal
522	Ethiopia	570	Seychelles Islands
525	Djibouti	571	Sierra Leone
526	Gabon	573	Somalia
527	The Gambia	575	Namibia
529	Ghana	580	St. Helena
531	Guinea	582	Swaziland
533	Cote d Ivoire (formerly Ivory Coast)	585	Tanzania
535	Kenya	588	Tunisia
537	Liberia	590	Uganda
538	Libya	591	Arab Republic Of Egypt
541	Madagascar	597	Zambia

Middle East

WAC	Description	WAC	Description
605	Bahrain Island	658	Oman
611	Cyprus	664	Qatar
632	Iran	667	People's Democratic Republic Of Yemen
634	Iraq	670	Saudi Arabia
636	Israel	676	Syrian Arab Republic
639	Jordan	678	United Arab Emirates
644	Kuwait	679	Turkey
647	Lebanon	694	Yemen

Asia

WAC	Description	WAC	Description
701	Afghanistan	757	North Korea
703	Bangladesh	764	Pakistan
704	Brunei	766	Philippines
706	Myanmar	770	Russia (Asian)
707	British Indian Ocean Territory-UK	776	Singapore
709	Democratic Kampuchea (Cambodia)	778	South Korea
713	China	781	Taiwan
729	Hong Kong-China	782	Thailand
733	India	785	Turkmenistan
736	Japan	786	U.S.S.R. (Asian)

Table B. List of Countries by World Region *(Continued).*

Asia (Continued)

WAC	Description	WAC	Description
744	Laos	788	Uzbekistan
747	Macau	791	Vietnam
749	Malaysia		

Oceania

WAC	Description	WAC	Description
802	Australia	844	Marshall Islands
804	Papua New Guinea	845	Nauru
810	Micronesia	846	New Caledonia - France
812	Cocos Islands-Australia	851	New Zealand
813	Cook Islands-New Zealand	852	Niue-New Zealand
821	Fiji Islands	874	Solomon Islands
823	French Polynesia	881	Tonga
824	Kiribati (Gilbert and Canton Islands)	892	Western Samoa
832	Indonesia		

Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/.

Appendix C: Regression Models to Forecast Passenger Enplanements from the U.S. to each World Region

Table C1. Estimated Model to Forecast Passenger Enplanements from the U.S. to Africa.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.924[a]	.854	.829	39476.048	1.311

a. Predictors: (Constant), Dummy, Ln_Africa_GDP

b. Dependent Variable: Africa_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-11595219	1610575		-7.20	.000		
	Dummy	-132533.3	38418.584	-.635	-3.45	.005	.360	2.8
	Ln_Africa_GDP	907889.24	123766.6	1.350	7.335	.000	.360	2.8

a. Dependent Variable: Africa_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.1E+011	2	5.459E+010	35.033	.000[a]
	Residual	1.9E+010	12	1558358348		
	Total	1.3E+011	14			

a. Predictors: (Constant), Dummy, Ln_Africa_GDP

b. Dependent Variable: Africa_Pax

Final Model:

$$APT_{U.S.\_Africa\_t} = -11,595,219 + 907,889 LnGDP_{Africa\_t} - 132,533 D_{911\_t}$$

Where:

$APT_{U.S.\_Africa\_t}$ = Total Air Passenger Trips from U.S. to Africa in Year *t*

GDP_{Africa_t} = Africa Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for $t < 2001$, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Table C2. Estimated Model to Forecast Passenger Enplanements from the U.S. to Asia.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.908[a]	.824	.795	703924.230	1.506

a. Predictors: (Constant), Asia_GDP, Dummy

b. Dependent Variable: Asia_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-5767990	2061050		-2.8	.016		
	Asia_GDP	2.182	.297	1.370	7.36	.000	.422	2.4
	Dummy	-2927403	632840.6	-.862	-4.6	.001	.422	2.4

a. Dependent Variable: Asia_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.8E+013	2	1.395E+013	28.161	.000[a]
	Residual	5.9E+012	12	4.955E+011		
	Total	3.4E+013	14			

a. Predictors: (Constant), Asia_GDP, Dummy

b. Dependent Variable: Asia_Pax

Final Model:

$$APT_{U.S.\_Asia\_t} = -5{,}767{,}990 + 2.182GDP_{Asia\_t} - 2{,}927{,}403D_{911\_t}$$

Where:

$APT_{U.S.\_Asia\_t}$ = Total Air Passenger Trips from U.S. to Asia in Year *t*

GDP_{Asia_t} = Asia Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for t < 2001, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Table C3. Estimated Model to Forecast Passenger Enplanements from the U.S. to Canada.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.969[a]	.939	.929	301530.811	1.807

a. Predictors: (Constant), Canada_GDP, Dummy

b. Dependent Variable: Canada_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1647709	831228.3		-1.982	.071		
	Dummy	-1158067	294728.2	-.469	-3.929	.002	.357	2.80
	Canada_GDP	15.297	1.401	1.304	10.92	.000	.357	2.80

a. Dependent Variable: Canada_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.7E+013	2	8.383E+012	92.200	.000[a]
	Residual	1.1E+012	12	9.092E+010		
	Total	1.8E+013	14			

a. Predictors: (Constant), Canada_GDP, Dummy

b. Dependent Variable: Canada_Pax

Final Model:

$$APT_{U.S.\_Canada\_t} = -1,647,709 + 15.297 GDP_{Canada\_t} - 1,158,067 D_{911\_t}$$

Where:

$APT_{U.S.\_Canada\_t}$ = Total Air Passenger Trips from U.S. to Canada in Year *t*

GDP_{Canada_t} = Canada Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for t < 2001, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Table C4. Estimated Model to Forecast Passenger Enplanements from the U.S. to Caribbean & Central America.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.987[a]	.974	.972	268085.363	1.451

a. Predictors: (Constant), Caribbean_CA_GDP

b. Dependent Variable: Caribbean_CA_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-2205883	472259.4		-4.7	.000		
	Caribbean_CA_GDP	61.215	2.778	.987	22.0	.000	1.000	1.0

a. Dependent Variable: Caribbean_CA_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.5E+013	1	3.489E+013	485.467	.000[a]
	Residual	9.3E+011	13	7.187E+010		
	Total	3.6E+013	14			

a. Predictors: (Constant), Caribbean_CA_GDP

b. Dependent Variable: Caribbean_CA_Pax

Final Model:

$$APT_{\text{U.S.\_Caribbean \& Central America\_t}} = -2{,}205{,}883 + 61.215 GDP_{\text{Caribbean \& Central America\_t}}$$

Where:

$APT_{\text{U.S.\_Caribbean \& Central America\_t}}$ = Total Air Passenger Trips from U.S. to Caribbean & Central America in Year *t*

$GDP_{\text{Caribbean \& Central America\_t}}$ = Caribbean & Central America Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for t < 2001, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Table C5. Estimated Model to Forecast Passenger Enplanements from the U.S. to Mexico.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.983[a]	.967	.961	252356.729	1.389

a. Predictors: (Constant), Mexico_GDP, Dummy

b. Dependent Variable: Mexico_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-3900780	697738.7		-5.591	.000		
	Dummy	-744085	223787.5	-.265	-3.325	.006	.434	2.31
	Mexico_GDP	21.238	1.451	1.167	14.638	.000	.434	2.31

a. Dependent Variable: Mexico_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.2E+013	2	1.117E+013	175.377	.000[a]
	Residual	7.6E+011	12	6.368E+010		
	Total	2.3E+013	14			

a. Predictors: (Constant), Mexico_GDP, Dummy

b. Dependent Variable: Mexico_Pax

Final Model:

$$APT_{U.S.\_Mexico\_t} = -3{,}900{,}780 + 21.238 GDP_{Mexico\_t} - 744{,}085 D_{911\_t}$$

Where:

$APT_{U.S.\_Mexico\_t}$ = Total Air Passenger Trips from U.S. to Mexico in Year *t*

GDP_{Mexico_t} = Mexico Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for $t < 2001$, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$)

Table C6. Estimated Model to Forecast Passenger Enplanements from the U.S. to Middle East.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.966[a]	.933	.921	48233.170	1.745

a. Predictors: (Constant), MiddleEast_GDP, Dummy

b. Dependent Variable: MiddleEast_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-941441	121814.7		-7.728	.000		
	Dummy	-267846	43424.72	-.712	-6.168	.000	.421	2.38
	MiddleEast_GDP	1.684	.140	1.390	12.04	.000	.421	2.38

a. Dependent Variable: MiddleEast_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.9E+011	2	1.934E+011	83.122	.000[a]
	Residual	2.8E+010	12	2326438694		
	Total	4.1E+011	14			

a. Predictors: (Constant), MiddleEast_GDP, Dummy

b. Dependent Variable: MiddleEast_Pax

Final Model:

$$APT_{U.S.\_Middle\ East\_t} = -941{,}441 + 1.684 GDP_{Middle\ East\_t} - 267{,}846 D_{911\_t}$$

Where:

$APT_{U.S.\_MiddleEast\_t}$ = Total Air Passenger Trips from U.S. to Middle East in Year *t*

$GDP_{Middle\ East\_t}$ = Middle East Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for t < 2001, D_{911_t} = 0, otherwise D_{911_t} = 1)

Table C7. Model to Forecast Passenger Enplanements from the U.S. to Oceania.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.906[a]	.821	.807	69869.583	1.669

a. Predictors: (Constant), Oceania_GDP

b. Dependent Variable: Oceania_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	487843.6	115153.9		4.236	.001		
	Oceania_GDP	2.032	.263	.906	7.721	.000	1.000	1.0

a. Dependent Variable: Oceania_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.9E+011	1	2.911E+011	59.621	.000[a]
	Residual	6.3E+010	13	4881758673		
	Total	3.5E+011	14			

a. Predictors: (Constant), Oceania_GDP

b. Dependent Variable: Oceania_Pax

Final Model:

$$APT_{U.S.\_Oceania\_t} = 487{,}844 + 2.032 GDP_{Oceania\_t}$$

Where:

$APT_{U.S.\_Oceania\_t}$ = Total Air Passenger Trips from U.S. to Oceania in Year *t*

$GDP_{Oceania\_t}$ = Oceania Real GDP of Millions of 2000 U.S. Dollars in Year *t*

Table C8. Model to Forecast Passenger Enplanements from the U.S. to South America.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.983[a]	.966	.961	158451.014	1.373

a. Predictors: (Constant), Dummy, SAmerica_GDP

b. Dependent Variable: SAmerica_Pax

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-4599310	441127.9		-10.426	.000		
	SAmerica_GDP	7.000	.390	1.158	17.961	.000	.678	1.47
	Dummy	-726633	112353.1	-.417	-6.467	.000	.678	1.47

a. Dependent Variable: SAmerica_Pax

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.6E+012	2	4.306E+012	171.527	.000[a]
	Residual	3.0E+011	12	2.511E+010		
	Total	8.9E+012	14			

a. Predictors: (Constant), Dummy, SAmerica_GDP

b. Dependent Variable: SAmerica_Pax

Final Model:

$$APT_{U.S.\_South\ America\_t} = -4{,}599{,}310 + 7.000GDP_{South\ America\_t} - 726{,}633D_{911\_t}$$

Where:

$APT_{U.S.\_South\ America\_t}$ = Total Air Passenger Trips from U.S. to South America in Year *t*

$GDP_{South\ America\_t}$ = Europe Real GDP of Millions of 2000 U.S. Dollars in Year *t*

D_{911_t} = Dummy Variable for 911 Terrorist Attack in Year *t* (for $t < 2001$, $D_{911\_t} = 0$, otherwise $D_{911\_t} = 1$

Appendix D: Assumed Airport Market Share by World Region

(Source: U.S. DOT BTS, T-100 International Segment Data in 2004, http://www.transtats.bts.gov/)

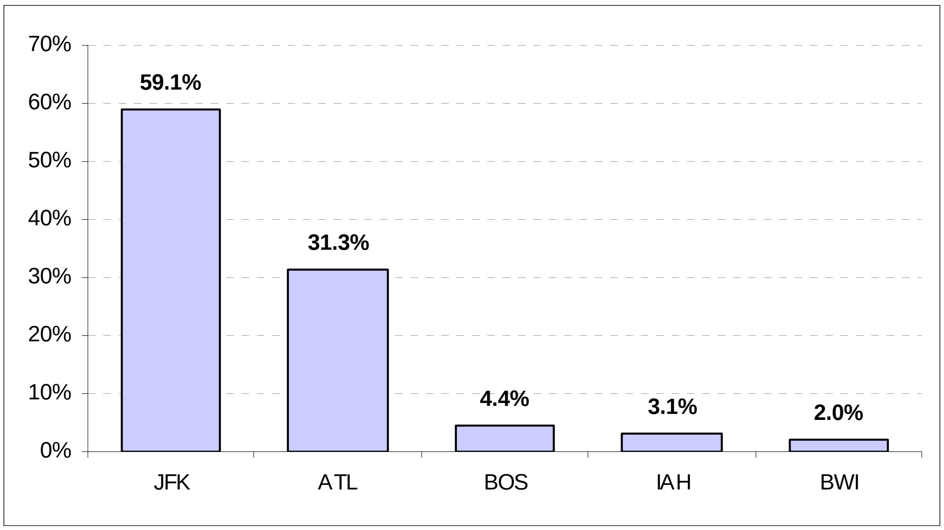

Figure D1: Assumed Market Share of Selected U.S. Airports to Africa.

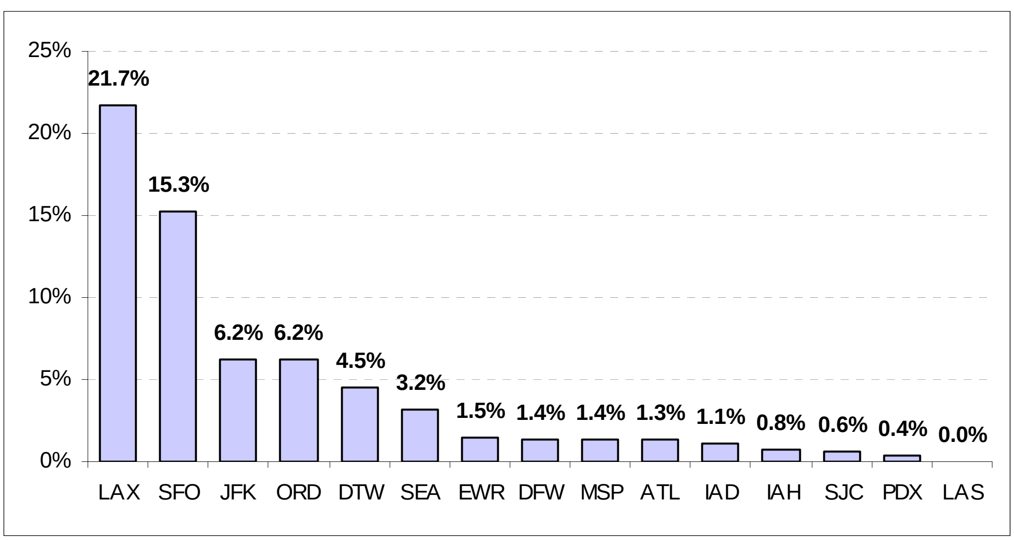

Figure D2: Assumed Market Share of the Top 15 U.S. Airports to Asia.

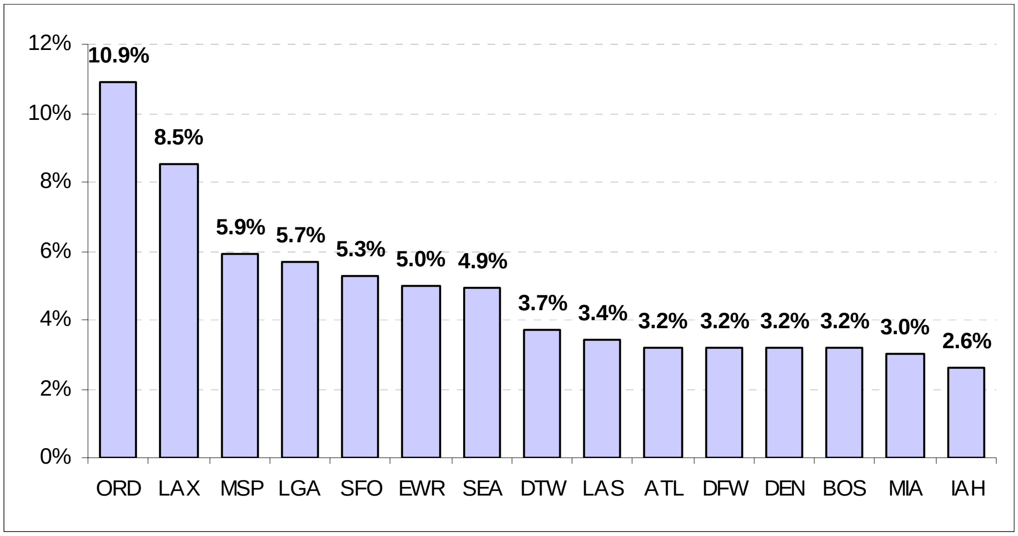

Figure D3: Assumed Market Share of the Top 15 U.S. Airports to Canada.

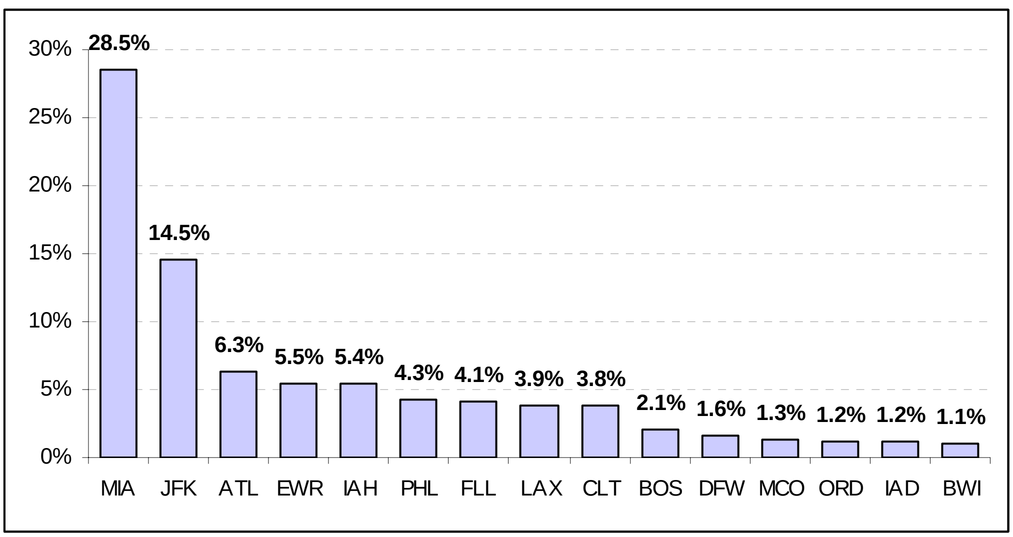

Figure D4: Assumed Market Share of the Top 15 U.S. Airports to Caribbean & Central America.

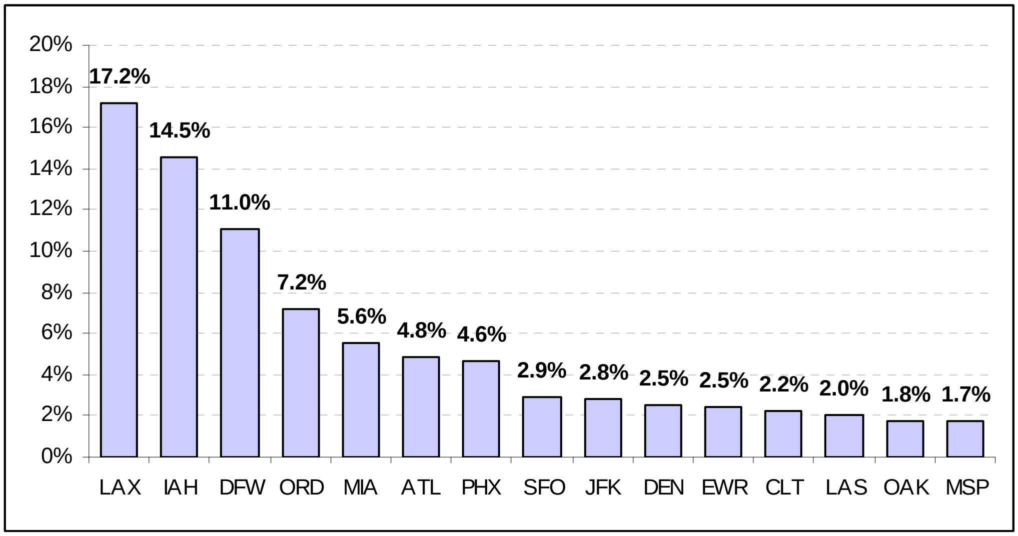

Figure D5: Assumed Market Share of the Top 15 U.S. Airports to Mexico.

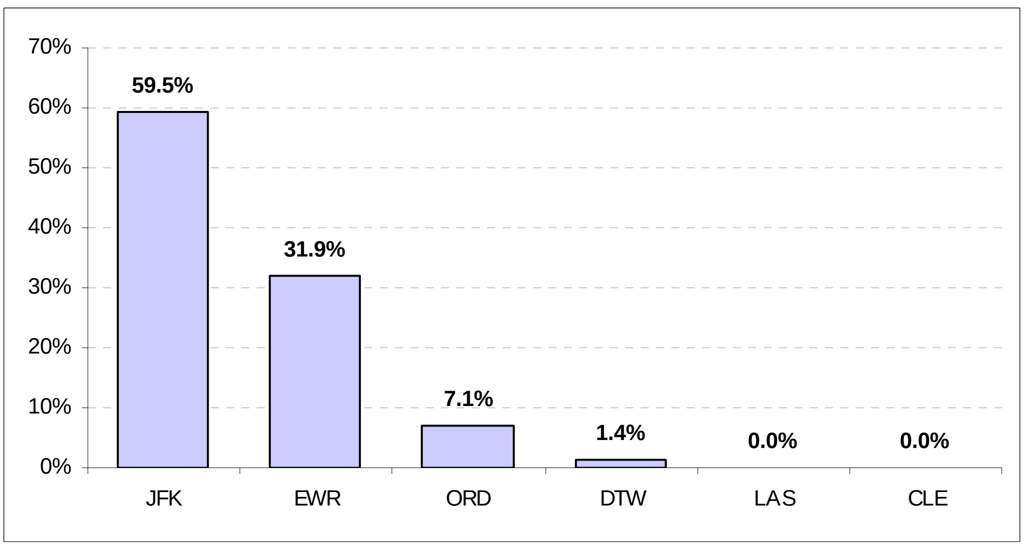

Figure D6: Assumed Market Share of the Top 6 U.S. Airports to Middle East.

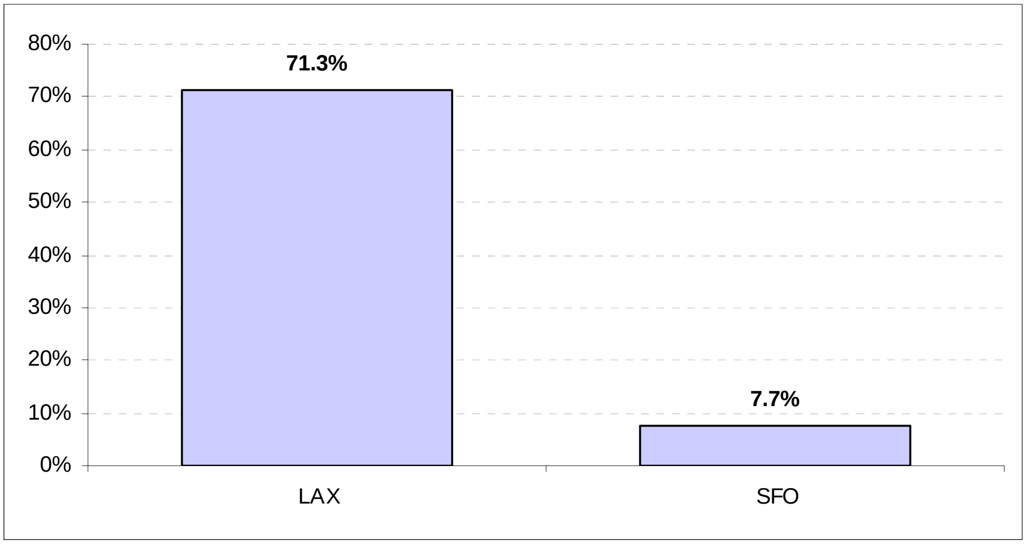

Figure D7: Assumed Market Share of the Top 2 U.S. Airports to Oceania.

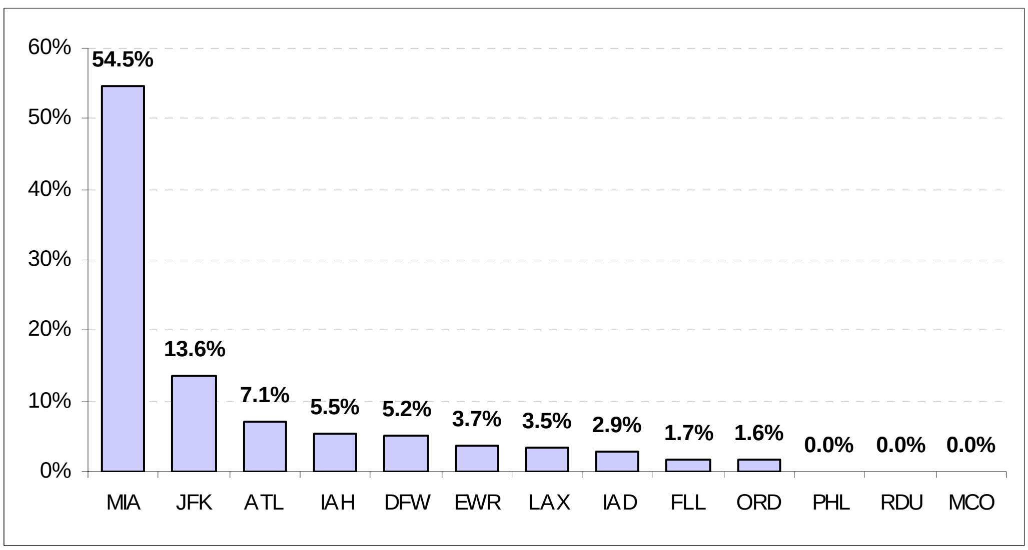

Figure D8: Assumed Market Share of the Top 15 U.S. Airports to South America.

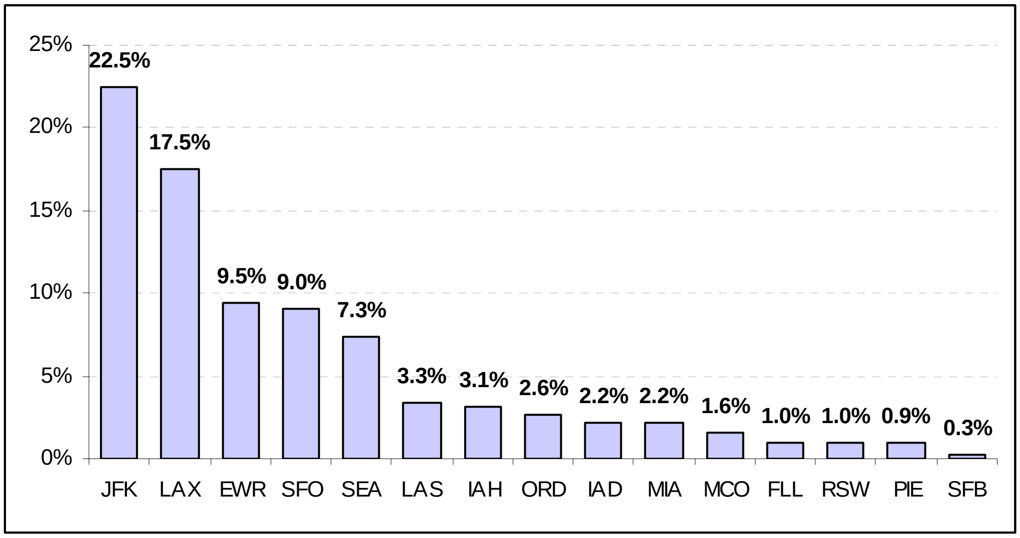

Figure D9: Assumed Market Share of the Top 15 Airports to U.S. International.