Demand and Capacity Problems in the Next Generation Air Transportation System

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ABSTRACT

This thesis investigates two main aspects of air transportation system, demand and capacity. The first study aims to estimate the potential market for Zip Vehicles, an advanced commuter type of aircraft equipped with automation and electric propulsion technologies. A Multinomial Logit Model was developed to estimate the mode choice behavior of commuters between Zip vehicle, auto and transit in seven metropolitan areas in the United States. The results showed that the Out-of-Vehicle travel time plays an important role in the decision process of commuters. Zip Vehicle is predicted to achieve residual demand with the current technologies and could become more competitive if it was equipped with Vertical Take-Off Technology. The second study developed a hybrid airport runway capacity model that blends both deterministic and simulation techniques. The model includes a graphic user interface that allows high degree of freedom to modify input parameters, such as airport information, weather conditions, minimum separation distances and aircraft grouping system. The model is widely validated and it appears to be a consistent solution for estimating airport capacity at different levels and with various degree of extensibility

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This section would not be complete without a special note of thanks to my sister, family members and friends all around the world for their unconditional support and confidence in me. Last but not least, I dedicate this thesis to my parents who have sacrificed a lot to see me accomplish this and whose love helped me fulfill it. Thank you.

Attribution Page

The demand part of this thesis (Chapter 2) is a conference paper that was presented at the 2015 Aviation conference. The author of this thesis was the main author and presenter of the paper but Dr. Antonio Trani and Nicolas Hinze assisted in the project.

Mr. Hinze, a senior researcher in the Air Transportation Systems Laboratory (ATSL) at Virginia Tech, assisted with the calculation of average distances and times from Census tracts and airports in the seven metropolitan areas in the study. He also helped integrating the demand study into the TSAM model developed by the ATSL at Virginia Tech.

Dr. Trani, faculty member of the Civil and Environmental engineering department at Virginia Tech, is the main investigator of the project with NASA Langley and provided continuous advices and guidance towards the completion of the project.

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1. Introduction

Air transportation is a complex system that has a major impact on worldwide economies. The main components of this transportation system are airports, airlines, air traffic control and aircraft. Each of these components can be studied by many disciplines, from engineering to planning and from economics to finance. All aspects need to be taken into consideration in order to have an efficient and safe system.

In this thesis, we focus on two aspects of air transportation: demand and capacity. In a fast-paced growing air transportation system, it is important to understand the current and potential demand of new concepts of operation and their effect in the aviation industry, such as a new aircraft or the future demand of an airport. The budgets of many projects depend on the predicted demand because an accurate forecast can reduce costs and time on projects that might not be necessary. In addition, understanding the capacity of an airport is critical to develop expansion plans and investigate cost to users and safety issues.

Mode Choice Model – Demand Estimation

This study investigates the potential market for Zip Vehicle, an advanced commuter type of aircraft equipped with automation and electric propulsion technologies with no pilot or perhaps single-pilot operations. Zip technology is thought of as an alternative to large regional commuting trips by auto or transit.

The approach taken in this process starts with the construction of a Multinomial Logit Model (MLM) model calibrated using the National Household Travel Survey database (2009). The calibrated model coefficients are used to estimate the probability that commuters choose one of three alternatives: Auto, Transit and Zip Aircraft. The process of demand estimation using the MLM model was carried out in parametric form assuming a range of ZIP aircraft costs.

The Multinomial Logit Model is calibrated for three attributes – Travel Cost, In-vehicle Travel Time and Out-of-Vehicle Time- included in the utility functions. The Out-of-Vehicle Travel Time seems to play an important role in the decision process since the calibrated coefficient was significantly higher than the other two variables. Therefore, we further refined the Out-of-Vehicle Travel Time variable by using the average transfer times between airports and population centers represented by Census tracts. We used a weighted procedure whereby the Census tract population acts as weight factor.

In this study, we estimated the potential demand in the New York and Southern California areas if the Zip Aircraft is converted to Vertical Take-Off and Landing (VTOL) technology. A paper for this study has been presented at the 2014 Aviation conference in Atlanta, GA.

The author of this thesis was the main researcher in this project. He conducted the literature view, analyzed the NHTS database, constructed the logit model with all its inputs, calibrated the model and analyzed the results. In addition, the author has also investigated the potential demand for Zip vehicle if this new mode was equipped with VTOL technology.

Airport Capacity Model

Responding to the need for NASA Langley to have a model that can quickly estimate runway capacity at an airport, this study developed an airport capacity model that estimates the throughput capacity of an airport. The throughput capacity is defined as the maximum rate at which an airport is able to operate landings and takeoffs without delays.

A literature review was conducted to have a better understanding of the currently available models in the market. We looked into numerous types of models, from a simple, but effective, FAA Airfield Capacity Model to the more sophisticated RunwaySimulator, developed by the Mitre Corporation.

The runway capacity model developed in this study estimates airport capacity for 250 airports in the United States contained in the Airspace Concept Evaluation System (ACES) NASA developed simulation model. The model is conceived to handle complex runway configurations, as long as no more than three or four runways are dependent on each other at the same time.

The methodology used in this study includes elements of complex simulation models and the simplicity of analytical models. First, random arriving or departing flights are generated to create an ordered sequence of flights by using blocking rules and minimum separation distances. The headway between all aircraft created in the simulation is calculated and the capacity is therefore estimated analytically by taking the inverse of the expected headway of the simulated operations. The model takes into consideration multiple aspects that can affect runway capacity, including minimum runway length for each type of aircraft to safely operate on a runway, staggered parallel runways, simulation bias error control, presence of control tower and weather conditions.

The model has been developed using Matlab as computational engine and Visual Studio Pro for the graphic user interface. The structure of the model is such that a user can change default values for each airport and aircraft grouping system, as well as modify system-wide parameters such as airport operational regulations that reflect new technology.

In the end, the model outputs are portrayed in the form of Pareto diagrams and Excel spreadsheets, with information about each simulated aircraft operation.

The author of this thesis was the main researcher in this project. He conducted the literature view, developed and coded all the main scripts of the model. The default values of the model were in part developed by the author and in part estimated by other students in the Air Transportation System Laboratory (ATSL) at Virginia Tech, under the supervision of the author of this thesis. In addition, the author performed and supervised the validation and verifications of the model and made changes to the model accordingly. The Graphic User Interface was developed using the expertise of Nicolas Hinze, Senior Research Associate in the ATSL.

This thesis is structured as follows: Chapter 2 contains the reference for the conference paper presented at the 2014 Aviation conference, which summarized the model and key findings of the Zip vehicle demand model developed. Chapter 3 includes an overview of the runway capacity model developed. Lastly, Chapters 4 and 5 include our conclusions and recommendations.

2. Mode Choice Model

Abstract

This study aims to study the potential market for Zip Vehicles, an advanced commuter type of aircraft equipped with automation and electric propulsion technologies. A Multinomial Logit Model was developed to estimate the mode choice behavior of commuters in seven metropolitan areas in the United States. The demand for Zip aircraft - as a mode of transportation for daily commuting - was modeled jointly with Automobile and Transit as competing modes of transportation.

Nomenclature

α_i = model coefficients

AU = characteristics associated with automobile

AC = auto cost ($)

AT = average auto cost to/from transit

AcC = average parking and interstate toll ($)

AOR = auto occupancy rate

CPM = AAA cost per mile ($)

ϵ = random error

FA = average transit fares ($)

IVT = in-vehicle travel time (minutes)

LL_R = log-likelihood of the restricted model

LL_U = log-likelihood of the unrestricted model

OVT = out-of-vehicle travel time (minutes)

Pr(i) = probability of the decision-maker of choosing mode i

TC = travel costs ($)

TrC = transit cost ($)

TR = characteristics associated with transit mode

U_i = utility of alternative i

ZP = characteristics associated with ZIP aircraft

2.1. Introduction

A Zip vehicle Heroen is proposed as an advanced commuter aircraft, which provides "High-Speed Mobility through On-Demand Aviation". The typical ZIP aircraft is expected to be equipped with high-degree of automation and electric propulsion technologies with no pilot or perhaps single-pilot operations. Zip technology is thought of as an alternative to large regional commuting trips.

Forecasting the demand potential for a vehicle that is not flying and whose acceptance in automatic flying mode is a challenging task. Our approach to forecast the demand for Zip Aircraft is the use of a Multinomial Logit Model (MLM) to estimate the mode choice probability for different modes of transportation with known costs and performance characteristics.

The approach taken in this process starts with the construction of an MLM model calibrated using the National Household Travel Survey database (2009). The calibrated model coefficients are used to estimate the probability that commuters choose one of three alternatives: Auto, Transit and Zip Aircraft. The process of demand estimation using the MLM model was carried out in parametric form assuming a range of ZIP aircraft costs. Virginia Tech developed simple life cycle cost models of a hypothetical ZIP aircraft for NASA that show that using current technology assumptions, the price of operating a ZIP aircraft with a purchase price of $300,000 would vary from $1.65 to $0.75 per seat-mile (in 2012 dollars) depending on the cost of automation (if no pilot option is used) and the utilization rate of the aircraft. The life-cycle cost study provided a baseline of the ZIP aircraft economics that are achievable today assuming periodic, direct and indirect costs of a ZIP aircraft similar to those of modern single engine piston powered aircraft. However, in the study we also estimated demand using parametric cost levels at $0.5 and $1.0 per seat-mile to understand the impacts on demand if the operating and acquisition costs were driven down in the future.

The calibrated Multinomial Logit Model has shown that all three attributes – Travel Cost, In-vehicle Travel Time and Out-of-Vehicle Time- included in the utility functions are significant to commuters' mode choice decision. The Out-of-Vehicle Travel Time seems to play an important role in the decision process since the calibrated coefficient was significantly higher than the other two variables.

The paper results present ZIP technology demand estimates using conventional paved runways as well as helipads to demonstrate the vaue of VTOL technology in commuting trips.

The steps taken in this study can be summarized as follows:

1. Literature review of past studies related to mode choice models.
2. Study of different national databases to select the most suitable data for our study.
3. Construct a Multinomial Logit Model using real costs of travel (by auto and transit) in selected metropolitan areas in the United States.
4. Apply the model developed by introducing the ZIP aircraft as an alternative.
5. Compare the MLM results with previously calibrated models.

6. Enhance the model developed by calculating detailed average transfer times to and from candidate ZIP airports considering Census Tract centroids within the area in our study.

7. Estimate ZIP aircraft commuting demand using the Census tracts and the County-to-County workflow tables.

2.2. Literature Review

A good description of the state-of-the-art ZIP aircraft technology is included in Moore et al. (2013). The study describes the vehicle technology and describes an initial assessment of the ZIP aircraft potential demand using TSAM long-distance logit model. Many studies have been conducted in the past about using mode choice models to forecast daily commuter demand (Cambridge Systematics, Inc.; Bhat C. and Koppelman S., 2006) and at the nationwide level (Trani et al., 2007). Most transportation models consider mode choices auto and transit, only a few studies were expanded and included air transportation (Proussaloglou and Koppelman, 1998). An earlier effort to understand the potential of on-demand services using small aircraft was conducted by the Virginia Tech Air Transportation Laboratory as part of the SATS program (Trani et al., 2003).

The subject of using aircraft for daily commuting in the literature has not been the subject of many studies. Perhaps this is a reflection that in real life, the applications of using aircraft or flying vehicles for daily commute is limited to rotorcraft transporting passengers between airports in large metropolitan areas or regular citizens commuting in remote places like Alaska where the ground network is sparse. Examples of commuter applications of rotorcraft can be found in New York as far back as 1955, where air travelers using La Guardia Airport could ride Sikorsky S55 and S58 helicopters to commute to Idlewild Airport (today's John. F. Kennedy International Airport). The $4.50 introductory one-way fare at the time would have been equivalent to~ $40 today - cheaper than a taxi cab ride in New York today. For comparison, today a helicopter transfer between any of the New York airports (LGA, EWR and JFK) costs $1,850 ($370 per person) using a Bell 407 five-passenger helicopter (Heliny, 2013).

2.2.1. National Transportation Surveys

Before building a ZIP commuter model, we studied several national surveys and databases to obtain information about American households, their travel behavior and socio-economic characteristics. Two nationwide surveys were chosen for more in-depth analysis: a) the National Household Transportation Survey NHTS and b) the Census American Community Survey. In theory, these two survey supply useful travel behavior information with large number of observations, information about travel behavior of travelers, trip purpose, and socio-economic data of each family (household). The NHTS is a transportation specific database, where each household was asked to keep a one day log of all the trips they made. Therefore, it contains data about each single trip, such as purpose, mean of transportation, travel time, distance travelled, type of vehicle, etc. A absent in the survey data is the travel cost component of the trip. On the other side, ACS is a more generic database, with more socio-economic information about US households. The limiting factor of the ACS survey is the absence of single trip information including single travel distance, intermodal information, wait time and highway toll paid. Table 1 summarizes the advantages and disadvantages of the two national surveys

After further examination, where we tested the adequacy of the survey data for our study with several statistical analyses, it was decided to use the National Household Transportation Survey for the study.

Table 1. National Household Travel Service vs. American Community Service.

National Household Travel Service (NHTS)	American Community Service (ACS)
Distance to Work (miles) is one of the variables	No Distance to Work is provided, only the Public Use Microdata Areas (PUMA) of place to work
Data from 2009, 2001, 1995 surveys available	1, 3, and 5 year surveys available
Not Comparable with National Census survey	Comparable with the National Census survey
Family Income level only divided per categories	Family Income available
Each single trip database is available	Multiyear estimates potential issues
The single year 2009 has more observations than ACS	
Transit time and waiting time available	

2.3. Multinomial Logit Model

In order to estimate the probability of selecting one transportation alternative from a discrete set of alternatives, we employ a Multinomial Logit Model (MLM). This technique considers each individual in a group as a separate element, with different socio-demographic attributes and choice alternatives. A MLM can be transferred to different times and geographic locations and it's less tied to the estimation data.

The Multinomial Logit Model assumes that the decision rule between alternatives is calculated by maximizing a utility function, which is derived using characteristics of the individuals and the mode alternative attributes. Each individual will choose the alternative that maximizes his or her utility. Equations (1), (2), and (3) illustrate the utility functions employed in our analysis. For daily commuting, it is assumed that users have three transportation mode alternatives to choose from: Auto, Transit and air transportation based on a hypothetical Zip aircraft. The error ϵ accounts for the component of the utility that is not predictable (imperfect information, error in collecting data and exclusion of relevant variables to explain individual's behavior). Different distributions can be assumed for the random variable associated with the sum of these errors. The Multinomial Logit Model assumes a binomial distribution for the errors (so-called logistic distribution of errors). The utility function in this study is composed by three variables: In-vehicle travel time (IVT), Out-of-vehicle travel time (OVT) and Travel Cost (TC).

$$U_{AU} = \alpha_1 \, IVT_{AU} + \alpha_2 \, TC_{AU} + \alpha_3 \, OVT_{AU} + \varepsilon \quad (1)$$

$$U_{TR} = \alpha_1 \, IVT_{TR} + \alpha_2 \, TC_{TR} + \alpha_3 \, OVT_{TR} + \varepsilon \quad (2)$$

$$U_{ZP} = \alpha_1 \, IVT_{ZP} + \alpha_2 \, TC_{ZP} + \alpha_3 \, OVT_{ZP} + \varepsilon \quad (3)$$

The probability of choosing one of the three modes of transportation is the fraction of the utility of all the other alternatives. Equation (4) shows the numerical expression to estimate the probability of selecting a mode.

$$\Pr(i) = \frac{\exp(U_i)}{\exp(U_{TRi}) + \exp(U_{AU}) + \exp(U_{ZP})} \quad (4)$$

2.3.1. Model Input Data and Assumptions

In order to study the potential use of ZIP aircraft as a commuting mode of transportation, we selected seven large metropolitan areas in the United States. The metropolitan areas selected for the study are: Houston, Dallas, Los Angeles, New York, Bay Area, San

Diego, and Washington DC. The areas were selected because they contained enough samples in the NHTS survey. Large metropolitan areas contain long daily commutes that could be replaced by an affordable air transportation alternative such as the ZIP aircraft. In this preliminary analysis, it was decided to calibrate the MLM model employing work trips for commuters with no consideration for recreational trips. Using work trips and those commuter journeys that were less than 100 nm, the NHTS survey had 112,122 usable sample trips for the calibration. In the calibration of the model, two modes of transportation are considered: auto and transit. The number of observed commuting trips using air transportation was statistically insignificant (i.e., fewer than 50 trips). In fact, most of the air trips included in the NHTS survey were long-distance trips taken by the individuals surveyed on the days when the survey was administered. The number of observations available in every metropolitan area shown in Table 2.

Table 2. Auto/Transit Observations.

Category	DC area	NYC	LA	San Diego	San Francisco	Total
Auto	2,880	6,060	6,860	6,065	3,924	25,789
Public Transit	185	720	147	105	192	1,349

The following section illustrates how travel cost and travel times are calculated for the baseline model in this study.

Cost and Travel Time for Selected Mode of Transportation

In-vehicle travel time is one of the variables surveyed in the NHTS database. For the travel cost, external analysis to the survey was conducted to estimate driving and transit costs. For auto cost, we used national average cost per mile from the American Automobile Association (AAA). Typical toll and parking fees were added in the analysis. The total cost was then divided by the average auto occupancy rate, as shown in Eq. (5). Table 3 shows the auto cost per mile for various urban areas considered in the study.

$$\mathrm{AC} = \frac{\mathrm{CPM} + \mathrm{AcC}}{AOR} \tag{5}$$

Transit costs in each metropolitan area are derived using the latest transit information. Using public transit web sites we derived cost functions based on travel distance for each metropolitan area. Equation (6) shows how transit fare costs were calculated. Transfer costs to and from transit stations were added for individual who drove or were dropped at a transit station.

Out-of-vehicle travel time (OVT) is estimated using different variables included in the NHTS survey. A wait time is added to the derived transfer time to and from transit terminals/stops/parking lots. For auto riders, out-of-vehicle travel time is estimated to be 2.5 minutes to account for the time it takes to walk to the parking lot/garage and from the parking lot to work. For transit riders, three variables contained in the NHTS survey are used to estimate OVT. Finally, wait time and the transfer times are given in the NHTS survey.

Table 3. Auto Travel Cost Table for Various Urban Areas.

Travel Cost		Costs Per Mile* ($)				
FIPS code	CMSA FIPS for HH address	Small/ Medium Sedan	Large Sedan/ SUV	Minivan	Interstate Tolls (two ways) ($)	Parking/ day ($)
1922	Dallas--Fort Worth, TX	0.50	0.70	0.62	1.48	3.70
3362	Houston-Galveston-Brazoria, TX	0.50	0.70	0.62	1.85	6.48
4472	Los Angeles--Riverside--Orange County, CA	0.50	0.70	0.62	4.63	9.72
5602	New York-Northern New Jersey-Long Island,NY-NJ-CT-PA	0.50	0.70	0.62	4.63	23.15
7320	San Diego, CA	0.50	0.70	0.62	3.70	8.10
7362	San Francisco - Oakland - San Jose, CA	0.50	0.70	0.62	9.26	17.36
8872	Washington DC	0.50	0.70	0.62	5.56	12.04

*(fuel, maintenance, tires, insurance, license, registration, taxes, depreciation, finance) - 15,000 miles per year

The baseline year of NHTS survey was 2009. Auto costs and fares were estimated for that year or converted to 2009 using the Consumer Price Index from the Bureau of Labor Statistics. The CPI index was found to be 1.08 to convert between fares in 2013 and those in the year 2009.

$$TrC = FA + AT \qquad (6)$$

Cost and Travel Time for Alternative Modes of Transportation

In order to successfully calibrate a Multinomial Logit Model, for each trip instance considered, an equivalent utility function (travel times and travel costs) was calculated for trips taking the mode of transportation not chosen. In the NHTS survey, respondents estimated travel time characteristics of the mode selected. To estimate travel times and costs for the modes not chosen we use a synthetic travel time and cost calculation method.

In-Vehicle-Travel Times

Transit Trips: we used an average auto speed calculated using observations from the NHTS survey. A reduction factor was applied to the distance to work because travelers tend to park closer to their final destination compared to transit. Table 4 shows the average auto speeds calculated from NHTS for each urban area.

Auto Trips: we used an average transit speed calculated using the real observations from the NHTS survey. A detour factor was applied to the distance to work because it has been found that travelling by transit would take the traveler farther than for the equivalent auto trip.

Table 4. Average Auto Speed for Various Metropolitan Areas (mph).

Dallas	Houston	Los Angeles	New York	San Diego	San Francisco	Washington DC
29.98	28.69	26.99	27.70	29.23	27.15	29.54

Out-Vehicle-Travel Times

Transit Trips: it was estimated an average OVT time for each urban area (see Table 5).

Auto Trips: we used a scaled time value ranging from 0.5 to 5.0 minutes according to the total time travelled. This value counts for the time spent to commute to and from parking lots.

Table 5. Average Intermodal Time per Metropolitan Area (minutes).

Dallas	Houston	Los Angeles	New York	San Diego	San Francisco	Washington DC
19.49	26.05	24.75	23.18	21.10	22.66	25.41

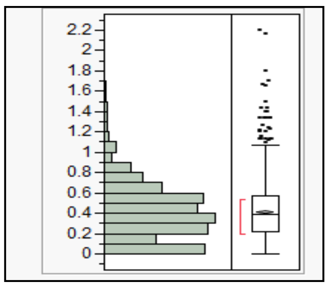
Travel Cost

Auto Trips: travel cost was estimated using Eq. (5). A detour factor of 1.2 was applied to the travel distance calculated.

Transit Trips: Equation (6) and the values shown in Table 4 were used to calculate auto travel costs for transit trips. Since no parking and toll fees information are available, a factor of 0.5 to all observations for both average daily parking fares and daily tolls was applied.

To verify that our assumptions were reasonable, Figure 1 shows a ratio between Out-of-Vehicle and In-Vehicle time for transit observations in the NHTS database:

- 75% of transit trips have an intermodal travel time within 56% of their travel time.
- The intermodal time of 90% of transit trips is within 75% of travel time



Summary Statistics	
Mean	0.4112813
Std Dev	0.2869347
Std Err Mean	0.0073767
Upper 95% Mean	0.425751
Lower 95% Mean	0.3968116
N	1513

Figure 1. Relationship between OVT and IVT travel time.

2.4. Model Calibration

The calibration of the Multinomial Logit Model was performed using the Multinomial Discrete Choice (MDC) procedure built in the SAS 9.3 software (SAS, 2013). This procedure estimates the coefficients of the utility functions using Maximum Likelihood Methods.

The data estimated from NHTS database had to be transformed into a single data set and with a specific format accepted by the software package.

2.4.1. Statistical Test and Goodness of Fit

As shown in Fig. 2, the estimated parameters by the baseline model are all significant at a high level of confidence. As expected, as the travel time and travel cost increase, the total utility for the commuter decreases. Goodness-of-Fit measures such as Estrella, McFadden and Veall-Zimmermann - scored above 0.90, and very close to 1. This means that the variables in our model predict well the mode choice decision of commuters.

The SAS System

The MDC Procedure

Conditional Logit Estimates

Parameter Estimates						
Parameter	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Alternative_Number	1	0.2788	0.1569	1.78	0.0756
Travel_Time	1	-0.0498	0.001859	-26.79	<.0001
Travel_Cost	1	-0.2105	0.007518	-28.00	<.0001
Intermodal_Travel_Time	1	-0.1986	0.006961	-28.53	<.0001

Figure 2. Output of the Baseline Model.

A statistical test was applied to compare two models: the first model is the "null model" where all parameters are set to be zero; the second model contains the calibrated coefficients for IVT, OVT and travel cost. The test-statistic in Eq. (7) is distributed along a chi-square distribution.

$$-2*[LL_R - LL_U] \quad (7)$$

The results of the test can be found in Table 6. With a critical value of 16.27, the null hypotheses can be rejected with high confidence. Time, cost and intermodal travel time are all statistically significant and thus cannot be excluded from the model.

Table 7 shows various parameters of the calibrated model including the ratio of travel time and travel cost. The ratio between travel time and travel cost is $14.19/hr., which is in good agreement with other urban transportation studies. In general, it has been found in many transportation studies that commuters under-value their value of time while commuting.

As we expected, commuters are very sensitive to Out-of-Vehicle Travel Time when choosing their mode of transportation to work. According to the calibrated model, the equivalent value of time for Out-of-Vehicle travel time is 56.60 $/hr. or 4.0 times the value of the In-Vehicle travel time.

Table 6. Likelihood Ratio Test.

Variables	
Log-likelihood of the unrestricted model (LLu)	-3,133
Log-likelihood of the null model (LLnull)	-20,494
Test Statistics (-2*[LLnull – LLu])	35,632
Number of Restrictions	3
Rejection Confidence	99.99%
Critical Chi-Squared Value	16.27

Table 7.Ratio between Calibrated Parameters of the Model.

Parameter	Baseline Model
IVT/TC ($/hr)	14.19
OVT/TC ($/hr)	56.61
IVT/OVT	3.99

2.4.2. Family Income Level

Analysis of NHTS data shows that commuting behaviors are significantly different across different income levels. More affluent families are more likely to travel slightly longer commute distances and therefore spend more time in the journey to work. To include different Income Groups in this analysis, the baseline model was calibrated multiple times, one calibration for each income group level.

Table 8 shows the calibrated coefficients. As expected, higher income level households are more sensitive to travel time and intermodal time, -0.06 to -0.012 and -0.18 and -0.14, respectively. Travel time cost per hour increases as the income level increases, which is also expected because more affluent families value their time higher than lower income groups.

The out-of-vehicle travel time seems highly important for the low-income group, 7.5 times the In-Vehicle travel time. The same ratio yields 3.0 for the highest income group (Income >100k$). This is very likely due to the scarcity of transit observations in our analysis. In fact, when the observations are divided into 5 groups, there are two to three hundred observations left for each income group. For this reason, many of the computations performed in the follow up sections are carried out using one average income model.

Table 8. Calibrated Coefficients for Five Income Groups.

Parameter	Baseline Model	FAMINC1 <29,999$	FAMINC2 30,000$ - 54,999$	FAMINC3 55,000$ - 79,999$	FAMINC4 80,000$ - 100,000$	FAMINC5 >100k$
Transit Observations	940	123	121	144	107	391
Auto Observations	28,626	2,301	3,869	5,459	3,626	12,071
% Transit Observations	3%	5%	3%	3%	3%	3%
Travel Time	-0.05	-0.02	-0.04	-0.06	-0.03	-0.06
Travel Cost	-0.21	-0.12	-0.17	-0.26	-0.15	-0.24
Out-of-Vehicle	-0.20	-0.15	-0.21	-0.27	-0.27	-0.18
Intercept	0.28	-0.01	0.62	1.41	1.80	-0.28
TT/TC ($/hr)	14.19	9.59	12.83	15.01	12.68	15.15
IT/TC ($/hr)	56.61	72.23	71.99	62.78	104.14	45.22
IT/TT	3.99	7.53	5.61	4.18	8.21	2.99

2.4.3. Comparison with Previous Studies

A comparison of the analysis presented in previous sections with past studies was conducted to gage similarities and differences. The results of Value of Time (VOT) obtained in the calibration suggests that our model compares well with previous urban transportation studies. For example, a large study done in Texas entitled "NCTCOG Mode Choice Model Estimation" administered a survey to commuter riders. The NCTCOG study used Logit Models for mode choice behavior in the region. The study used a daily trip database collected in 1996 and compared both nested and non-nested Multinomial Logit models.

The ratio of out-of-vehicle time/in-vehicle time in the NCTCOG and other urban areas models varies between 1.5 and 3. In the model calibrated by this study, the ratio OVT/IVT was 3.9. Considering that the NCTCOG model used as baseline a survey dated 1996, it is not surprising that after more than ten years commuters could value their transfer and idle time higher than before. The value of time for the NCTCOG and Other Urban Areas was estimated to be between $2 to 5$ in 1996 dollars. Our model predicts a value of time closer to the wage average.

Bhat and Koppelman (2006) offers some insight in the coefficients of a logit model calibrated using survey data for the San Francisco Bay area. In this more recent study, the value of time increases monotonically with income level. The values of time predicted by Bhat and Koppelman fluctuate from $4.5 to $21.9 per hour in the baseline model and is less volatile when the Log of Income is taken. The values calculated from our study are between $9.6 and $15.1 per hour, which is well within the boundaries estimated by Bhat and Koppelman and it is also less volatile.

The IVT and OVT values calculated by Bhat and Koppelman range between $0.3 to $2.2 and $7.8 to $9.5, respectively. These figures are low considering the average wage in their area of study. The ratio between OVT and IVT varies between 2.5 and 4.0, while the same ration calculated by our study is 3.9.

2.4.4. MLM Model Runs with ZIP Aircraft Technology

To introduce the ZIP aircraft into our model, we first assumed deterministic performance parameters shown in Table 9. The ZIP aircraft is assumed to have a cruise speed of 130 mph. The parameters selected assume a block speed of 100 mph. This includes taxi-in and taxi-out times that could be short for this class of vehicle. More analysis will be needed to factor in congestion effects in a dense terminal area and subject to limited capacity constraints. For this first-order analysis we assumed 20 minutes of out-of-vehicle travel time. This time is the combination of waiting for the vehicle at the ZIP airport and also includes processing time.

Table 9. Zip Vehicle Deterministic Parameters.

Parameter	Value
ZIP Speed	100mph
In-Vehicle Travel Time	Distance/ZIP Speed
ZIP Cost ($)	Distance*Zip Cost/mile
Zip Cost/mile($)	0.5, 1.0, 1.5
Out-of-Vehicle Travel Time	20 minutes

Figure 3 illustrates shows a flowchart to perform the mode choice analysis including the calculations required for the ZIP aircraft model. Note that the flowchart iterates across all observations in the NHTS survey and Eq. (4) was used to determine the probability of selecting one of the three alternatives (Auto, Transit and ZIP Aircraft). Table 10 illustrates the outcome of this first-order analysis. After introducing the ZIP aircraft mode, auto continues to be the predominant mode of transportation with and average market share of 90%. Low-income level groups have the highest probability to commute by transit. Zip aircraft is more likely to be used by high-income level families. A $0.5 per seat-mile, the ZIP aircraft mode could capture 8.1% of the high-income level commuter trips. Note that a value of $0.5 per seat-mile is actually cheaper than auto travel cost and this is considered unfeasible with current aviation technology. Nevertheless, it is instructive to examine the variations in ridership with ZIP aircraft cost per seat-mile over a range of values.

Table 10. Mode Choice Probabilities.

Mode of Transportation	Probability		
	Cost $0.5/mile	Cost $1.0/mile	Cost $1.5/mile
Auto	90.39%	94.06%	94.66%
Transit	4.08%	4.61%	4.68%
Zip Vehicle	5.53%	1.34%	0.66%

The cost per set-mile increases monotonically, the probability of choosing Zip Vehicle decreases in a non-linear fashion. According to the model calibrated, at a cost of $1.5 per seat-mile the ZIP aircraft market share would be around 0.66% instead.

The next stage of the study focused at refining the estimates of out-of-vehicle time and distance. The transfer distances to and from airport are now assumed to vary between 1 and 15 miles. The average speeds shown in Table 4 are used to calculate the transfer time to and from the ZIP aircraft landing sites (ZIP airports). According to the calibrated model, Out-of-Vehicle travel time has a major impact on the commuter’s mode choice. As the Out-of-Vehicle distance increases by even one mile, the probability of using ZIP aircraft drops considerably. Figure 4 illustrates the potential demand for ZIP aircraft as a function of intermodal distance (i.e., access distance to an airport).

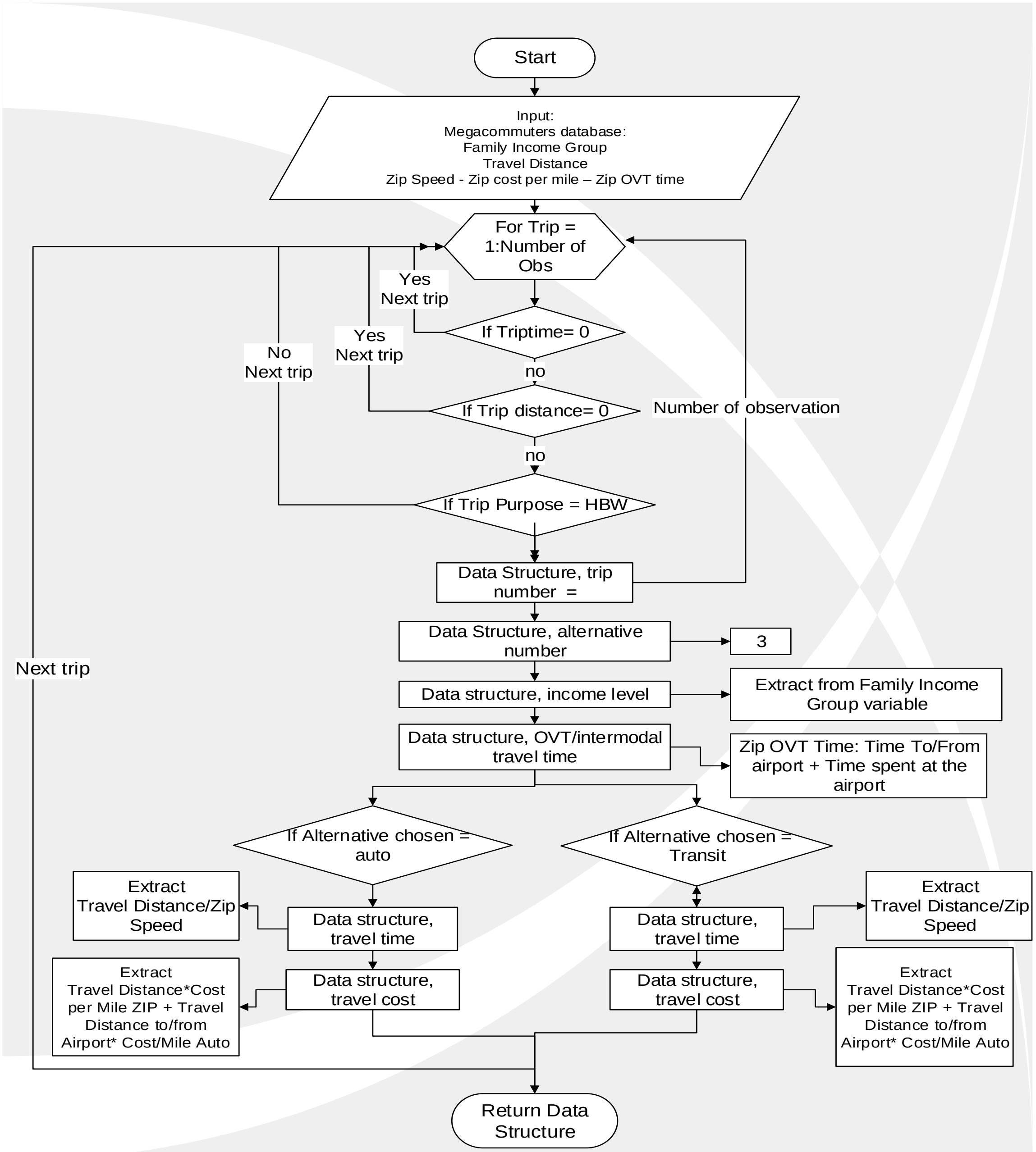


Figure 3. Flowchart Outlining the Zip Vehicle Data Structure Heuristic.

To estimate the potential number of commuters in seven metropolitan areas of the study, we employed CENSUS workflow tables (2006-2010), which contain the number of people that commute from one county to another every day. The probabilities of choosing one of the three modes of transportations were calculated for each one of our metropolitan areas and the results are shown in Table 11. New York has the highest number of potential commuters with more than 80.000 trips by Zip Vehicle if the transfer to/from airport was 3 miles.

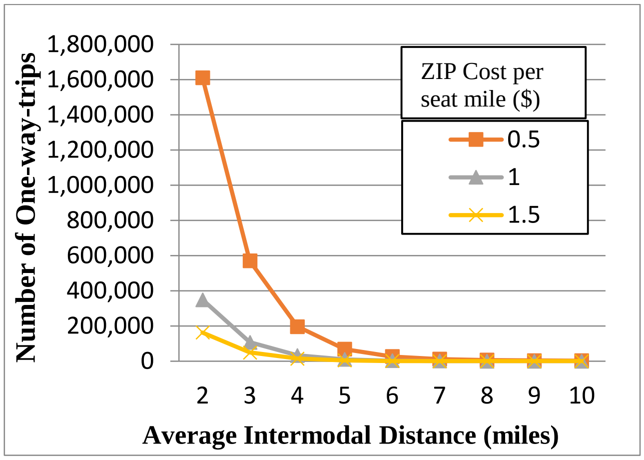


Figure 4. ZIP Aircraft Market Share vs. Access Intermodal Distance.

Table 11. ZIP Aircraft Mode Choice Trips by Urban Area.

# of Trips	Trasfer To/From Airport Distance		
Zip Cost/mile $1	3	5	7
Model	178,108	16,409	1,506
Dallas--Fort Worth, TX	11,679	1,183	120
Houston-Galveston-Brazoria, TX	10,793	998	93
Los Angeles--Riverside--Orange County, CA	35,920	3,035	257
New York-Northern New Jersey-Long Island,NY-NJ-CT-PA	84,373	7,702	684
San Diego, CA	6,743	652	63
San Francisco - Oakland - San Jose, CA	24,748	2,121	181
Washington DC	24,497	2,421	239

2.4.5. Refinement of ZIP Aircraft Analysis

In this section, we further refine some of assumptions made about the mode and its accessibility to ZIP airports. This refinement allows estimate time and distance to airports more realistically. Moreover, the analysis presented in this section considers the population at each Census tract and the employment centers in metropolitan areas to estimate average travel distances and commuting times.

Table 12 shows a summary of the total number of tracts and airports within each metropolitan area studied. Note that for this analysis, San Diego and Los Angeles are merged into one metropolitan area realistic view of commuting.

To understand the average transfer times between airports and Census tracts, we used a weighted procedure whereby the Census tract population acts as weight factor.

The same technique was applied to the calculation of transfer times from the airport to workplace. An average driving time from each airport to each Census tract at the county level is calculated by using the attractiveness (number of jobs) of each tract as weight. The average driving time of the area is estimated using as weights the percentage of commuters to each county.

Table 12. Potential ZIP Airports and Census Tracts for Each Metropolitan Areas.

Zip Vehicle Refinement - Transfer to/from airport			
Urban Area	**Census Tracts**	**All Airports***	**Filtered Airports****
Dallas--Fort Worth, TX	1,312	213	47
Houston-Galveston-Brazoria, TX	1,183	115	42
Southern California - Los Angeles/San Diego, CA	4,879	123	79
New York-Northern New Jersey-Long Island, NY-NJ-CT-PA	5032	125	54
Bay Area, CA	2,232	70	46
Washington DC area, DC-VA-MD-WV	2,186	142	42
*Data from Federal Aviation Administration (FAA) Only GA airports with less than 300 commercial flights per year **Only airports with paved runways and a runway with at least 2,000 ft. length.			

To further refine the analysis we considered an airport set that would represent potential aircraft airports that could handle a low power loading, wing loading vehicle.

Considering that ZIP aircraft would have to operate as a reliable model of transportation for commuting, we identified public airports with a paved runway of at least 2,000 feet in length as a realistic set of ZIP aircraft airports.

Table 12 (“Filtered Airports’ column) shows the total number of airports in each metropolitan area after the new filter is applied. As expected, in most of areas we observe a large trimming effect if the 2,000 foot runway. For example, in the Dallas-Fort Worth area the number of airports is reduced from 213 to 47, while in the New York area less than 50% of the airpots survived the cut.

Table 13 shows the average distances from the ZIP airports to the job and population centers in each area selected.

Table 13. Potential ZIP Airports and Census Tracts for Each Metropolitan Areas.

	Average Time To Airport (min)		Average Time From Airport (min)				Average Distance To Airport (miles)		Average Distance From Airport	
Summary	All Airports	Filtered Airports*	Filtered Airports	Baseline Scenario	Total Jobs	Total Population	Filtered Airports	Baseline Scenario	Filtered Airports	Baseline Scenario
Dallas, TX	14.9	18.3	15.9	18.1	2,854,460	6,275,377	7.5	9.2	7.9	9.1
Houston, TX	20.1	21.8	22.3	23.9	2,654,802	6,213,857	9.6	10.4	10.7	11.4
South California	31.0	31.0	32.9	33	8,607,986	22,139,695	14.5	14.5	15.4	15.5
NYC Area	29.3	30.6	28.5	29.5	9,676,852	22,721,091	13.5	14.1	13.2	13.6
Bay Area, CA	18.1	18.7	18.3	18.9	4,154,762	10,034,183	8.2	8.5	8.3	8.6
Washintgon DC	22.8	26.4	24.6	27.2	4,047,434	8,787,740	11.3	13.0	12.1	13.4
* For runway length			**Total**		31,996,296	76,171,943				

From Table 13 (“Filtered Airports” columns) we can derive important trends:

- The average time from an airport to the workplace is longer than the average time from a residential area to the airport. Business centers are usually further away from GA airports than residential areas.
- South California and New York areas have around 30% each of the total number of jobs of the areas selected..
- New York area and Southern California have high average driving time/distance to and from airports. This can be explained by the heavy traffic encountered within these areas and for the case of Southern California. The region covers a very large area, which increases driving time between activity centroid pairs.
- The average time to get to an airport and from an airport to any workplace in the Dallas and Bay Area is approximately 18 minutes. Almost half of the driving times estimated for New York and Southern California areas.

Using the calibrated coefficients explained in the previous section, the model was executed to estimate the mode choice probabilities for three transportation modes. Table

14 shows the results of the MLM model using the refined airport-level assumptions. Overall, the ZIP Aircraft is predicted to attract a small market 0.01% of commuters when ZIP cost is $0.5 per seat-mile and less than 0.001% when the cost per mile is $1, which translates into 5,461 and 159 total daily trips, respectively. The San Francisco Bay Area seems to capture most of the Zip Aircraft demand (3,360 out of 5,461 trips when the ZIP cost/mile is 0.5$), this is because the same region has a low estimated average time to/from airports. Auto remains by far the most heavily used mode of transportation, while Transit has a 5% market share in three metropolitan areas: New York (7.70%), Bay Area (5.19%) and Washington DC (6.81%).

The market share figures of this refined estimation show that for ZIP aircraft to be more competitive, we have to reduce the Out-of-Vehicle travel time, which plays a key role in the decision process of mode choice for a commuters. However, the estimated average transfer time to/from airports is very high for almost all urban areas in our study. As shown in Fig. 5, in the New York area there are almost no GA airports in the proximity of Manhattan and surrounding counties, where most of the people and jobs are located. In fact, it would be inconvenient for commuters to fly from home to an airport that is still 30-40 minutes away from where their job place. The same issue is found in other Urban Areas.

The Zip Vehicle is expected to use a 2,000 feet runway length, but this requirement will not be enough to support a substantial demand for this technologically advanced aircraft. One feature that could increase the demand is the use of Vertical Take-Off and Landing (VTOL) technology. In fact, if Zip Vehicles were to take-off and land vertically, then not only airports but also helipads could be used for commuting.

Table 14. Mode Choice Results Using Refined Potential ZIP Airports.

ZIP Cost: 0.5$ (Seat/mile)	All Areas	Dallas	Houston	Los Angeles	NY Area	San Diego	San Francisco	DC Area
Auto	95.98%	97.61%	96.76%	98.13%	92.30%	97.47%	94.77%	93.19%
Transit	4.01%	2.38%	3.24%	1.85%	7.70%	2.53%	5.19%	6.81%
ZIP	8.23E-05	3.17E-05	4.09E-06	0.02%	3.70E-07	5.13E-08	4.04E-04	7.72E-07
Daily # of working trips	66,345,990	5,708,920	5,293,564	16,771,314	19,353,704	2,814,096	8,309,524	8,094,868
Zip Trips	5461	181	22	3173	7	0	3360	6

ZIP Cost: 1$ (Seat/mile)	All Areas	Dallas	Houston	Los Angeles	NY Area	San Diego	San Francisco	DC Area
Auto	95.99%	97.62%	96.76%	98.15%	92.30%	97.47%	94.81%	93.19%
Transit	4.01%	2.38%	3.24%	1.85%	7.70%	2.53%	5.19%	6.81%
ZIP	2.39E-06	6.00E-06	7.06E-07	6.42E-09	5.36E-08	1.28E-08	1.22E-05	1.12E-07
Daily # of working trips	66,345,990	5,708,920	5,293,564	16,771,314	19,353,704	2,814,096	8,309,524	8,094,868
Zip Trips	159	34	4	0	1	0	101	1

In the New York Area, there are 250 helipads that are privately and publicly owned but not used for medical or public security (police and fire stations) reasons. The use of these helipads and those airports that were previously filtered out because of their runway length could improve ridership for zip vehicles. The average transfer Time is calculated again for the NY area and not surprisingly, the transfer time to airports dropped to be 13.4 minutes, while the average transfer time from airports to workplace is 11.3 minutes. The average transfer distance both ways is now 11.4 miles. Even if we consider only GA helipads (see purple marks in

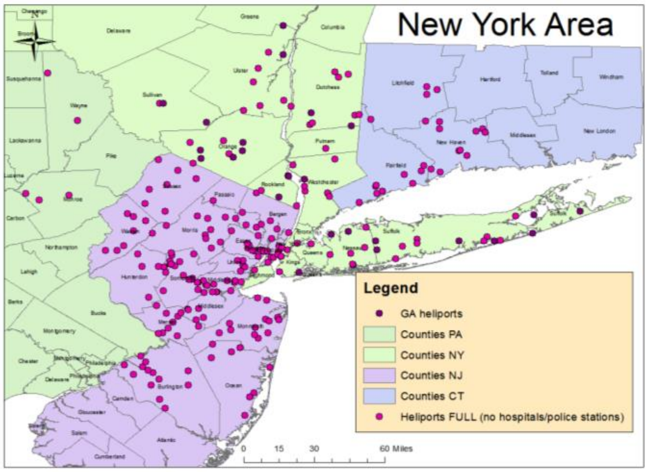


Figure 5. Helipads in New York Area.

Fig. 4), the average transfer to/from airports is lower than previous analysis with just airports (see Table 15). Moreover, Helipads are closer to densely populated Urban Areas. When our calibrated is run again, Zip Vehicle would attract 0.63% of the commuters, which estimated to be around 121,448 people if Zip Cost is $0.5 seat/mile and around 21,284 people if Zip Cost is $1.0 seat/mile (see Table 16). A significant increase compared with previous analysis, where the demand was close to zero. Zip Vehicle must be very competitive if it wants to attract demand, since public transit is well developed and efficient in most metropolitan areas.

Table 15. Mode Choice Demand for New York Area – Summary Table.

Wait Time 15 minutes	GA airports /w paved runway >2,000 ft.	All GA airports	GA airports + all heliports*	GA airports + GA heliports*
ZIP Cost: 0.5$	New York Area			
Auto	92.30%	92.30%	91.82%	92.29%
Transit	7.70%	7.70%	7.56%	7.70%
ZIP	3.70E-07	6.57E-07	0.63%	8.66E-06
Daily # of working trips	19,353,704	19,353,704	19,353,704	19,353,704
Zip Trips	7	13	121,448	168

ZIP Cost: 1.0$	New York Area			
Auto	92.30%	92.30%	92.21%	92.29%
Transit	7.70%	7.70%	7.68%	7.70%
ZIP	5.36E-08	9.46E-08	0.11%	1.24E-06
Daily # of working trips	19,353,704	19,353,704	19,353,704	19,353,704
Zip Trips	1	2	21,284	24
* no medical or security (poice and fire stations) use				

Table 16. Average Transfer to/from Airports for New York Area – Summary Table.

		Average Time To Airport (min)	Average Time From Airport (min)	Average Distance To Airport (miles)	Average Distance From Airport (miles)	Total Average Distance (miles)
GA airports /w paved runway >2,000 ft.	New York Area	30.6	29.5	14.1	13.6	27.7
All GA airports	New York Area	29.3	28.5	13.5	13.2	26.7
GA airports + GA heliports*	New York Area	25.5	26.0	11.8	12.0	23.8
GA airports + all heliports*	New York Area	13.4	11.3	6.2	5.2	11.4

* no medical or security (poice and fire stations) use

The same calculations were executed for the South California area, where 204 helipads and 35 GA helipads were included in the analysis, as shown in Fig. 6. Table 17 shows that with the introduction of helipads, the average transfer time to/from airports drops from more than half an hour to 22/23 minutes in the case of full set of helipads and to 26/27 minutes if we consider only GA heliports.

The intense congestion in the area still keeps the transfer time high but the demand more than doubled if helipads are included in the analysis, as illustrated in Table 18.

The analysis shows that that South California area is very sensitive to a change in the travel cost. If fact, when the same calculations are executed with the Zip cost at $1.0 per seat/mile, the demand for Zip Vehicle drops to zero in all scenarios. This is due to the Transit Travel Cost function that was applied in the calculation of the utility function. The Los Angeles area has a very large territory where it is difficult to derive a single cost function

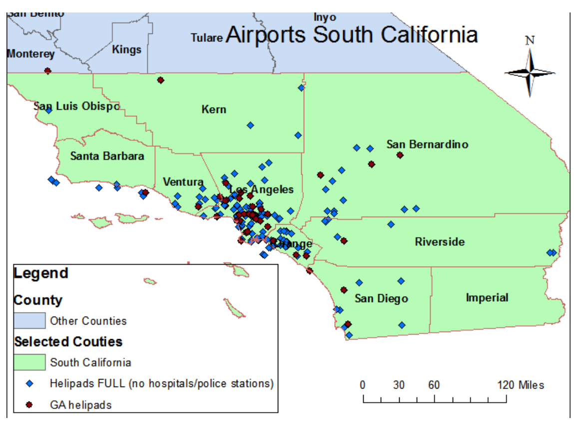


Figure 6. Helipads in South California.

to estimate the transit costs from the distance travelled by a commuter. Therefore, it was decided to use a parametric cost function, where for each distance travelled it was associated a specific travel cost.

Table 17. Mode Choice Demand for Southern California – Summary Table.

Wait Time 15 minutes	GA airports /w paved runway >2,000 ft.	All GA airports	GA airports + all heliports*	GA airports + GA heliports*
ZIP Cost: 0.5$	Southern California			
Auto	98.13%	98.13%	98.10%	98.11%
Transit	1.85%	1.85%	1.85%	1.85%
ZIP	0.02%	1.90E-04	0.05%	0.03%
Daily # of working trips	16,771,314	16,771,314	16,771,314	16,771,314
Zip Trips	3173	3179	8014	5472
ZIP Cost: 1.0$	Southern California			
Auto	98.15%	98.15%	98.15%	98.15%
Transit	1.85%	1.85%	1.85%	1.85%
ZIP	0.00%	6.71E-09	0.00%	0.00%
Daily # of working trips	16,771,314	16,771,314	16,771,314	16,771,314
Zip Trips	0	0	30	4
* no medical or security (poice and fire stations) use				

Table 18. Average Transfer to/from Airports for Southern California – Summary Table.

		Average Time To Airport (min)	Average Time From Airport (min)	Average Distance To Airport (miles)	Average Distance From Airport (miles)	Total Average Distance (miles)
GA airports /w paved runway >2,000 ft.	Southern	31.03	33.00	14.53	15.46	29.99
All GA airports		31.00	32.87	14.52	15.39	29.91
GA airports + GA heliports*		26.13	27.89	12.24	13.06	25.30
GA airports + all heliports*		22.54	23.70	10.56	11.10	21.66
* no medical or security (poice and fire stations) use						

Nevertheless, the inclusion of helipads definitely showed that more demand is generated for Zip Vehicle across both metropolitan areas studied. Helipads are closer to more densely populated metropolitan areas, where it is more difficult to find airports with runways of more than 2,000 feet.

2.5. Conclusion

The calibrated Multinomial Logit Model has shown that all three attributes – Travel Cost, In-vehicle Travel Time and Out-of-Vehicle Time- included in the utility functions are significant in the commuters' mode choice decision. The Out-of-Vehicle Travel Time plays a critical role in the commuter travel decision process since the calibrated coefficient was significantly higher than the travel cost and in-vehicle travel. time.

The predicted demand for Zip Vehicles is low for both $0.5 and $1.0 seat/mile travel cost. This is driven by the high average transfer time to/from airports calculated for each urban area in our study. Since the Zip Vehicle would require a 2,000 feet runway for take-off and landing operations, most commuters would have to drive, on average, more than 20-25 minutes each way to reach an airport and to their workplace from an airport. The competition with auto and transit in our model makes the Zip Vehicle unattractive to commuters and therefore the ridership is predicted to be low.

Ultimately, this study estimated the potential demand in the New York area if the Zip Aircraft is converted to VTOL technology. The results showed that the average transfer time from/to airports dropped from more than half an hour to 11 minutes, which leads to a more competitive Zip Vehicle.

A. Further Studies.

Using more sophisticated methods to calculate travel time and travel cost can enhance the baseline model. For instance, the Los Angeles area resulted too sensitive to a chance in the Travel Cost, which is due to the parametric way on calculating Transit Travel Cost.

A lack in observations limited the analysis of this study. Unfortunately, no further studies including different income groups were possible. One way to solve this issue is to include more metropolitan areas in the study, so more observations and wider sets of airports and helipads become available.

As an alternative, stochastic process methods can be used to include family income level in the study, such as Monte Carlo simulations.

There is a lack of GA airports near the main Metropolitan Areas, such as New York City, DC, Dallas, etc. Not only there are no GA airports in the most densely populated areas, but most of the times also close by counties lack of adequate infrastructures for Zip Vehicles. For example, Manhattan in New York City does not have airports with 2,000 paved runways, but also the Bronx County and the whole area northern Manhattan are lacking of airports for Zip Vehicles with fixed wing technology. The same reasoning applies to DC, Houston and Dallas area.

We believe that the demand for Zip Vehicles would increase if Vertical Take-off (VTOC) technology is adopted.

A mode choice model based on a database such as the NHTS first order analysis of possible demand for Zip Vehicle. Further refinements would involve collecting survey data using hypothetical commuter trips with inclusion of zip vehicle cost and travel time estimates. Commuters can be questioned directly whether they would be willing to take this new commuting aircraft and under what conditions, with the aim of including ZIP aircraft perceived reliability and desirability.

Citation for the conference paper of this study:

Pu D., Trani A., Hinze N. (2014). "**Zip Vehicle Commuter Aircraft Demand Estimate: a Multinomial Logit Model Choice Model**". 14th AIAA Aviation Technology, Integration, and Operations Conference. America Institute of Aeronautics and Astronautics. http://arc.aiaa.org/doi/abs/10.2514/6.2014-2411

3. Quick Response Runway Capacity (RunSim) model

Abstract

The Federal Aviation Administration predicts a constant growth of airport operations in the next two decades to satisfy demand. Airports will have to maximize capacity by containing costs and minimizing delay. The deployment of NextGEN technologies requires models and tools to evaluate capacity benefits in the National Airspace System (NAS). In this scenario, there is a need for airport capacity models that can quickly estimate airport capacity but still providing good level of accuracy. The objective of this project is to develop a computed model to estimate airport capacity using a hybrid model that blends analytical and simulation techniques. The model developed uses Matlab as the computational engine and includes a graphic user interface developed in Visual studio. The model allows a high degree of freedom to modify input parameters, such as airport information, weather conditions, ATC minimum separation standards and aircraft grouping system.

The model is validated using airport operational data and the output appears to be consistent with previous airport capacity studies.

3.1. Introduction

The U.S. Department of Transportation Federal Aviation Administration's (FAA) forecasts[1] a constant growth of 2.8 percent of passengers flying each year for the next two decades. Compared to the 750 million passengers in 2014, the expected number of passengers flying on U.S. airlines in 2034 is expected to be 1.15 billion. In parallel to passenger enplanements, air cargo traffic is also expected to more than double by 2034. All these numbers lead to an increase of more than 10 million landings and takeoffs in 2034 compared to 2013, reaching a staggering number of almost 62 million operations at FAA-operated and FAA contract towers. In this scenario of constant growth, airport capacity forecast and constraints play a critical role in the improvement and safety of the national airport/airspace system. Airports will need to maximize the use of available runway capacity to minimize delays. Reduced delays decrease airline costs and improve passenger level of service. At the federal level, the deployment of NextGen technologies requires models and tools to evaluate capacity benefits in the National Airspace System (NAS).

The estimation of airport capacity is a complex issue. Multiple factors affect airport capacity, among them there are runway configurations, fleet mix, configuration of taxiways and number of gates. In addition, there might be airspace limitations such as arrival fix loading, sector loading, and human factors that can limit airport capacity. Other factors that influence capacity are air traffic control separation standards,

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[1] "**Press Release – FAA Forecast Sees Continued, Steady Growth in Air Travel.**" Federal Aviation Administration. March 13, 2014. http://www.faa.gov/news/press_releases/news_story.cfm?newsId=15935.

meteorological conditions, surveillance technology (radar) and the presence of air control towers.

The FAA provides two definitions[2] for airfield capacity:

- Throughput capacity: maximum rate at which an airport is able to operate landings and takeoffs without regard to any delay.
- Practical capacity: number of operations that an airport can accept considering average delay.

In this project, we develop a runway capacity model to estimate the throughput capacity of an airport. The uniqueness of this model is that includes elements of complex airport simulation models and the simplicity of analytical models. The goal is to estimate the capacity for 250 airports contained in NASA's Airspace Concept Evaluation System (ACES) simulation model. Random arriving and departing flights are generated to create an ordered sequence of flights by using blocking rules and minimum separation distances. The expected headway of all successive aircraft created in the simulation is then used to estimate the throughput capacity for the airport. The model takes into consideration multiple aspects that can affect runway capacity. For example, the model considers the requirement for the minimum runway length for all types of aircraft to safely operate on a runway. The model is also able to model staggered parallel runway operations and include simulation error control, the presence of a control tower and the weather conditions.

The model has been developed using Matlab as the computational engine and Visual Studio Pro to create a graphic user interface. The model structure is designed such that a

[2] Airport Cooperative Research Program. "**Evaluating Airfield Capacity".** *Report 79.* 2012

user can change default values for each airport and aircraft group, as well as modify system-wide parameters, such as airport operational regulations that reflect new technology. The model outputs are portrayed in the form of Pareto Diagrams and Excel spreadsheets, with information about each simulated aircraft operation.

The following sections of the report summarize the work. Section 2 includes a literature review related to other airport capacity models used in this field. Section 3 describes the runway capacity model developed in this study, including input parameters, output formats, algorithms used in the model, the graphic user interface developed and the verification and validation of the model. Lastly, we draw the conclusions and recommendations for future refinements of the mode in section 4.

3.2. Literature Review

This project started with a literature review about the different runway capacity models currently available. Kim & Hansen (2009) state that capacity models can be classified into different categories, according to various attributes of the model.

Calculation method:

- Analytically: mathematical representations of operations, calculated using a calculator or spreadsheet. The average time between operations (departures and/or arrivals) is calculated by using simple inputs that affect capacities.
- Simulation models:
  - Macroscopic: similar to analytic models but they use discrete-time steps and at each step the information is updated.
  - Microscopic: streams of aircraft are created and the model produces specific information for each single aircraft, such as the aircraft type and discrete times at which the aircraft crosses runway thresholds or intersecting points. These types of models are probably the more comprehensive but also the most complex ones.
  - Mesoscopic: combine elements of both macro and microscopic modes.

Stochastic capability:

- Deterministic: parameters of the model are deterministic
- Stochastic: parameters are treated as random variables

Scopes:

Depending upon their scope, airport capacity models can consider various capacity elements of an airport. These include the following factors: runway configuration, number of gates available, apron areas, taxiways and airspace.

3.1.1. Analytical Models

In this section, we describe some of the analytical models we reviewed: Airport Cooperative Research Program (Report 79), Enhanced Airfield Capacity Model and Runway Simulator.

Airport Cooperative Research Program (ACRP) Report 79

The Airport Cooperative Research Program (ACRP) Report 79 presented an Excel spreadsheet tool that provides a mechanism for calculating runway capacity defined as the maximum sustainable throughput of arrivals and departures. The model is simple and easy to use since it uses an environment that most people are familiar with but it only allows three runway configurations (single, two parallel and intersecting runways). The model was tested in our study and it proved to be unreliable. For example, the output table provides allocation of operations to each runway studied but often shows questionable results, such as no arrivals capacity for the second runway.

Enhanced Airfield Capacity Model (EACM)

The FAA first developed the Enhanced Airfield Capacity Model (ACM) in the seventies and then upgraded in the eighties to analytically calculate the capacity of an airport. The model has been widely used since its development because it provides a quick environment to predict runway capacity. Dr. J. Barrer at the Mitre Corporation developed a user-friendly interface in 1991. This model was used by numerous FAA studies including the FAA airport benchmark reports[3] and other models that came afterwards.

Runway Simulator

MITRE/CAASD developed a capacity model called RunwaySimulator. This simulation model enables rapid analysis of airport capacity by blending a package of different methodologies (analytical and simulation techniques). RunwaySimulator is coded in Java and it could be released to the public. This model was used to estimate future airport Capacity Benchmarks.

3.1.2. Simulation Models

Simulation models track in detail the movement of each aircraft throughout airspace and airport network. These programs are more accurate than their analytical counterparts are but they are usually costly and each scenario can take several days to develop and run. These usually also require a detailed schedule of flights for each airport. Examples of these models are SIMMOD Pro, Total Airspace and Airport Modeler (TAAM) and the Reorganized Mathematical Simulator (RAMS).

SIMMOD Pro

SIMMOD Pro is an advanced airspace and airport simulation model developed by ATAC and maintained by the FAA[4]. The model uses a node-link structure that allows simulating individual aircraft from the gate to the airspace routes. SIMMOD Pro comes with a user-friendly graphic user interface, a traffic animator to replay all aircraft movement and a feature that allows easy display and analysis of simulation output. The capability of

[3] U.S. Department of Transportation Federal Aviation Administration. "**Airport Capacity Benchmark Report 2004".**

[4] "SIMMOD Part 2." Accessed November 10, 2014. http://www.tc.faa.gov/acb300/more_simmod.asp.

SIMMOD Pro is not limited to runway capacity but it allows analysis for a wide range of airport and airspace queries, such as aircraft delay, airspace route structures, and traffic management techniques.

Total Airspace and Airport Modeler (TAAM)[5]

TAAM is developed by Jeppersen and it is claimed to be the first gate-to-gate simulator of airport and airspace operations. Remarkable features of this model include an advanced 3D graphic that enhances user experience and 4D (3D plus time) models to facilitate decisions for planning and analysis. TAAM allows randomization of model parameters and is capable of "what-if" scenarios to account for uncontrollable chances.

Reorganized ATC Mathematical Simulator (RAMS Plus)[6]

RAMS is a fast-time gate-to-gate simulation that was first introduced in 1995 by EUROCONTROL Experimental Center (ECC). The unique feature about RAMS plus is that it is an open agent component, which allows a third party to create and customize APIs for their own platforms.

3.2. ATSL Airport Capacity Model

This chapter illustrates the solution for airport capacity developed by this study.

The model employs a hybrid modeling approach. In fact, the model blends analytical and microscopic simulation techniques. Like other simulation models, a large number of external events are generated to create an ordered sequence of flights to be simulated. Each aircraft entity is assigned a group attribute (legacy, Recat or personalized group)

[5] "Total Airspace and Airport Modeler (TAAM)." Jeppesen. Accessed November 10, 2014. http://ww1.jeppesen.com/industry-solutions/aviation/government/total-airspace-airport-modeler.jsp.

[6] "Rams Plus." RamsPlus.com. Accessed November 10, 2014.

according to the fleet mix of the airport. The ordered sequence of aircraft can represent either arrival or departure operations.

First, all input parameters, default values and outputs for the model are presented. Afterwards, we illustrate the methodology used by the model, single steps to estimate capacity of an airport with single or multiple runways and how we control the error and bias of the simulation. In the end, we described the Graphic User Interface developed and the model validation undertaken.

3.2.1. Input Parameters

The capacity of an airport is dependent on multiple factors, and in this model we try to cover as many of these factors as possible. We can divide all inputs into 3 large families: aircraft grouping information and airport information and other advanced parameters.

Aircraft Grouping

This model treats aircraft classes in three different grouping systems:

- Legacy wake group includes five different wake classes: small, large, B757, heavy and super heavy
- Recat grouping system (Phase 1) is based on the FAA Advisory Circular 608 and it was first introduced at Memphis International Airport. In this grouping system aircraft are grouped into six different classes, from the largest aircraft (A) to the smallest (F), based on Minimum Take-off Mass (MTOW) and Wingspan.
- Personalized grouping system: the user has freedom to define a customized number of groups by defining the upper and lower bounds of the MTOW and wingspan of each group. This grouping system is useful, for example, when dealing with smaller airports that need more sub-groups for smaller types of aircraft.

Aircraft Group Specific Parameters

The Runway Capacity model requires different parameters for each aircraft group defined by a user. For each 186 different aircraft in the Base of Aircraft Data (BADA)[7] the following list of parameters are required:

- Runway occupancy time (ROT) (s)
- Annual usage (hours)
- Number of aircraft in circulation in the US
- Approach speed (knots)
- Minimum runway length (ft.)
- Maximum Takeoff Weight (lb.)
- Wingspan (ft.)

The average ROTs, Minimum runway lengths and approach speeds for each type of aircraft are found using the Performance Data Analysis and Reporting System[8] (PDARS) data, provided by the FAA partnered with the National Aeronautics and Space Administration (NASA).

The model assigns a group to each aircraft type in the BADA list and takes a weighted average for every aircraft in each group to define parameters such as ROTs (mean and standard deviation), approach speed, and minimum runway length for takeoff and

[7] "Eurocontrol - Driving Excellence in ATM Performance." Base of Aircraft Data (BADA). Accessed November 7, 2014.

[8] "Programs-Performance Data Analysis and Reporting System." Accessed November 8, 2014. http://www.atac.com/pdars.html.

landing. The weighted average is given by the annual hourly usage and number of active aircraft registered in the FAA registry[9].

Airport Default Values

The focus of the project is to define credible runway capacities for 250 airports contained in the NASA ACES model. For each airport, we estimated a set of default values in order to provide baseline values for quick analysis. First, we looked into the different types of aircraft that operate at the airport and whether a control tower is present at each airport, then we gathered information of the runway configuration and how the runways are most operated at each airport.

Fleet Mix

Different types of aircraft operate at each airport and this is important to acknowledge because the minimum separation between arrivals or departures depend on the type of aircraft simulated. In fact, small facilities usually operate only small type of aircraft, which require little separation distance between successive operations. On the other hand, airport with heavier types of aircraft usually operate less aircraft per unit of time because operations need to be more spaced out from each other. More homogeneous fleet mix also allow more capacity than a heterogeneous fleet mix because small aircraft need a large separation after heavy-types of aircraft. We estimated the fleet mix of each airport by using the FAA Air Traffic Activity System (ATADS) database[10].

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[9] "FAA REGISTRY." FAA Registry. Accessed November 7, 2014. http://registry.faa.gov/aircraftinquiry/acftref_inquiry.aspx.

[10] "Air Traffic Activity System (ATADS)." Air Traffic Activity System (ATADS). Accessed November 7, 2014. https://aspm.faa.gov/opsnet/sys/Main.asp?force=atads.

Airport Runway Information

Using the FAA Landing Facilities Database, it was extrapolated information about each single runway end of an airport:

- Runway End Label
- Latitude
- Longitude
- Magnetic Azimuth
- Runway Length (ft.)
- Runway Width (ft.)
- Displaced Threshold
- Elevation (ft.)

This information is used in the model to estimate separation and the type of interaction between runways. The airport elevation is also used to estimate the minimum runway length required for each type of aircraft to safely perform arrivals and departures.

Airport Runway Configuration

The runway configuration plays an important role to estimate the capacity of an airport. This includes understanding how the airport is operated in terms of which runways are used for arrivals and which ones for departures. In fact, this study provides the most representative runway configuration for each airport. The model is flexible allowing a user to specify any runway configuration by passing the provided default ones.

- For the 77 airports contained in the Aviation System Performance Metrics (ASPM)[11] data, the runway configuration is estimated using the most used arrival and departure runways declared by the airport itself.
- For the remaining airports, we conducted a study to predict the most likely used runway configuration using wind data, runway lengths and orientation.

Minimum Separation Distances

In this paragraph, we present the minimum separation distances for successive operations and the minimum separation rules to establish whether two or more runways can operate independently from each other.

Minimum separation distances for successive operations

Table 19 & Table 20 show the default values for minimum separation under IMC conditions between successive arrivals and departures, respectively. Each figure provides two tables for minimum separation distances for legacy wake and Recat grouping systems.

[11] "Aviation System Performance Metrics (ASPM)." Aviation System Performance Metrics (ASPM). Accessed November 7, 2014. https://aspm.faa.gov/apm/sys/main.asp.

Table 19. Minimum Arrival-Arrival Separation Distances for IMC Conditions. Values are nautical miles.

Legacy Wake	Small	Large	B757	Heavy	Super Heavy
Small	2.5	2.5	2.5	2.5	2.5
Large	4	3	2.5	2.5	3
B757	5	4	3	3	3
Heavy	6	5	4	4	3
Super Heavy	8	7	6	6	6

Recat	A	B	C	D	E	F
A	2.5	5	6	7	7	8
B	2.5	3	4	5	5	7
C	2.5	2.5	2.5	3.5	3.5	6
D	2.5	2.5	2.5	2.5	2.5	5
E	2.5	2.5	2.5	2.5	2.5	4
F	2.5	2.5	2.5	2.5	2.5	2.5

Table 20. Minimum Departure-Departures Separation for IMC Conditions. Values are in seconds.

Legacy Wake	Small	Large	B757	Heavy	Super Heavy
Small	60	60	60	60	60
Large	60	60	60	60	60
B757	120	120	120	120	120
Heavy	120	120	120	120	120
Super Heavy	180	180	180	180	180

Recat	A	B	C	D	E	F
A	60	180	180	180	180	180
B	60	120	120	120	120	210
C	60	60	60	120	120	180
D	60	60	60	60	60	120
E	60	60	60	60	60	60
F	60	60	60	60	60	60

Weather Conditions

Runway capacity is estimated for Visual Meteorological Conditions (VMC) and Instrumental Meteorological Conditions (IMC). Under VMC conditions, pilots have enough visibility, high enough cloud ceilings and clearances to see and maintain visual separation from terrain and other aircraft. With current technologies, the minimum separations maintained by pilots under VMC conditions are lower than the respective separations under IMC conditions. Anecdotal evidence shows that VMC separations are typically 10% below IMC conditions. This factor is used as a default value in the VMC analysis.

Control Tower

Having a control tower can influence the capacity of an airport. In fact, in a non-towered airport pilots follow recommended procedures in terms of arrival and departure patterns and may receive clearance from remote control centers. At non-tower airports, the minimum separation distances between operations are considerably larger compared to the separation used at IMC conditions. Our default values are:

IMC Conditions:

- Arrivals: 15-20 miles of in trail distance between successive arrivals
- Departures: FAA task order 7110 is be used to infer this information. Approximately, 3-10 minutes between successive departures

VMC Conditions:

- Arrivals: a multiplier of 1.3 will be applied to minimum separation matrix between successive arrivals with an ATC control tower (see Table 21)

Table 21. Minimum Separation Distance in VMC Conditions with NO Control Tower. Values are nautical miles.

Legacy Wake	Small	Large	B757	Heavy	Super Heavy
Small	3.25	3.25	3.25	3.25	3.25
Large	5.2	3.9	3.25	3.25	3.9
B757	6.5	5.2	3.9	3.9	3.9
Heavy	7.8	6.5	5.2	5.2	3.9
Super Heavy	10.4	9.1	7.8	7.8	7.8

Recat	A	B	C	D	E	F
A	3.25	6.5	7.8	9.1	9.1	10.4
B	3.25	3.9	5.2	6.5	6.5	9.1
C	3.25	3.25	3.25	4.55	4.55	7.8
D	3.25	3.25	3.25	3.25	3.25	6.5
E	3.25	3.25	3.25	3.25	3.25	5.2
F	3.25	3.25	3.25	3.25	3.25	3.25

- Departures: a multiplier of 1.3 will be applied to minimum separation matrix between successive departures when a control tower is available.

Minimum Separation Rules for Independent Operations

In order to establish whether two or more runways are independent from each other, this model uses minimum separation rules and by default, it provides the current minimum FAA separation rules. The following list provides the different rules that are implemented in the model:

Table 22. Minimum Separation Distances for Independent Operations.

Parameter Name	Description	Unit of Measure
Parallel Independent Arrivals -VMC	Minimum distance between the centerlines of two parallel runways to run independent arrivals under VMC conditions.	Feet
Parallel Independent Arrivals - VMC (legacy groups V-VI)	Minimum distance between the centerlines of two parallel runways to run independent arrivals under VMC conditions. If the airport operate aircraft groups V-VI	Feet
Parallel Dependent Arrivals	Minimum distance between the centerlines of two parallel runways to run dependent arrivals under IMC conditions with the diagonal distance approaches	Feet
Parallel Independent Arrivals	Minimum distance between the centerlines of two parallel runways to run independent arrivals under IMC conditions.	Feet
Parallel Dependent Departures	Minimum distance between the centerlines of two parallel runways to run independent departures under IMC conditions.	Feet
Parallel Stagger Rule	Minimum distance of two parallel runways with their runway thresholds offset todecreased/increased by 100 feet	Feet
Parallel Independent Arr-Dept	Minimum distance between the centerlines of two parallel runways to run independent departures on one runway and arrivals on the other one under IMC conditions.	Feet
3 Parallel Independent Arrivals (1000 ft. altitude)	Minimum separation distance between the centerline of three parallel runways to run independent arrivals. Airport elevation below 1000 ft.	Feet
3 Parallel Independent Arrivals (5000 ft. altitude)	Minimum separation distance between the centerline of three parallel runways to run independent arrivals. Airport elevation below 5000 ft.	Feet
4 Parallel Independent Arrivals	Minimum separation distance between the centerline of four parallel runways to run independent arrivals.	Feet

Parameter Name	Description	Unit of Measure
Crossing Path Dependency Rule	Dependency for two runways that have their extended centerlines intersecting (crossing paths runways)	Nautical Mile
Minimum Diagonal Distance Parallel	Minimum diagonal distance for arriving aircrafts on two close parallel runways	Nautical Mile
Minimum Intersect Arrival	For two intersecting runways, the minimum distance of one landing from its threshold when an arrival on the other runway has crossed the intersection or left the runway before the intersection	Nautical Mile
Min Arr-Dept Separation	The minimum distance between one arrival and one departure, and vice versa.	Nautical Mile
Min Arr-Dept Close Parallel Separation	The minimum distance between one arrival and one departure on two close parallel runways, and vice versa.	Nautical Mile

Runway Configuration Supported

The ACM is built to handle not only simple runway configuration but also more complex ones with 3-4 runways that are dependent from each other. The model detects at the beginning of each run the number of sets of dependent runways at the airport. The capacity of each set of dependent runways is then calculated independently and combined together using a numerical superposition rule.

Dependent runway configurations supported by the model:

a) Single runway

b) Two intersecting runways

c) Two Parallel runways

d) Two parallel and one intersecting runways

e) Four Runways (only for limited scenarios)

3.2.2. Model Outputs

The model outputs are portrayed in the form of a graph called Pareto Diagram and Excel spreadsheet with information about each simulated aircraft operation.

Pareto Diagram

The capacity of an airport is portrayed in the Pareto Diagram graph, as shown in Figure 7. The graph has “Departures per hour” on the x-axis and “Arrivals per hour” in the y-axis. Using different separation distances between landing operations, the model first calculates multiple points within the graph, where each Pareto point represents the maximum number of takeoffs and landings allowable. Consequently, the Pareto diagram is finalized by creating a convex function approximation of the Pareto points calculated in the simulation.

If there is more than one set of independent runways, then the Pareto diagrams are combined two by two using a numerical superposition method, which is simply the arithmetic sum of each point in one Pareto diagram with its equivalent point on the other Pareto diagram.

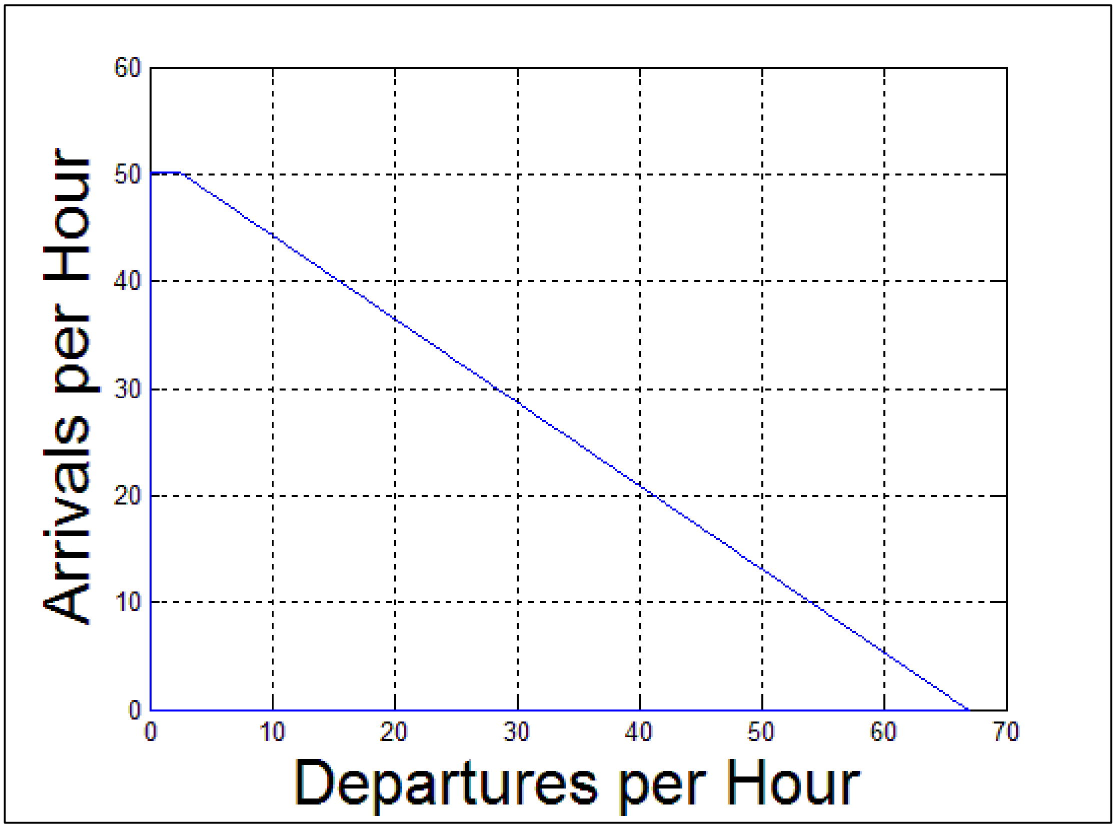


Figure 7. Model Output – Pareto Diagram.

Excel Spreadsheet

The model produces two Excel spreadsheets, one for arrival and one for departure operations. Each table provides information about each simulated aircraft operation. The arrival table shows for each aircraft the group type, time at runway threshold, ROT, time the plane exits the runway, time it crosses the intersection and runway end label. The departure table provides information for each aircraft the group type, time at runway threshold, ROT, time the plane is airborne, time it crosses the intersection and the runway end label.

3.2.3. Methodology

In this section, we describe the algorithms used in the model to estimate arrival and departure capacity. First, we estimate the input matrices required by the model from the parameters defined by the user. Second, we describe the rules and algorithms to calculate capacity for airports with single and multiple runways. Lastly, we explain how we control simulation error biases.

Estimation of Input Matrices Procedure

The first step of the model is to estimate input matrices that define separation distances between runways and the relation between runways. In fact, by comparing the azimuth and the possible intersection points of two runways, we calculated an interaction matrix that states whether two runways are parallel, intersecting or have crossing paths. Other input matrices are the distances between centerlines and stagger distances for parallel runways and distances to intersecting and crossing path points.

Once input matrices have been created, the model calculates the sets of runways that are dependent of each other by using the ATC minimum separation distances established by the FAA or defined by the user. The capacity of each set of dependent runways will be calculated separately and merged together at the end to obtain one single Pareto Diagram. For the complete runway configuration, Figure 8 shows each step to estimate the capacity of the airport.

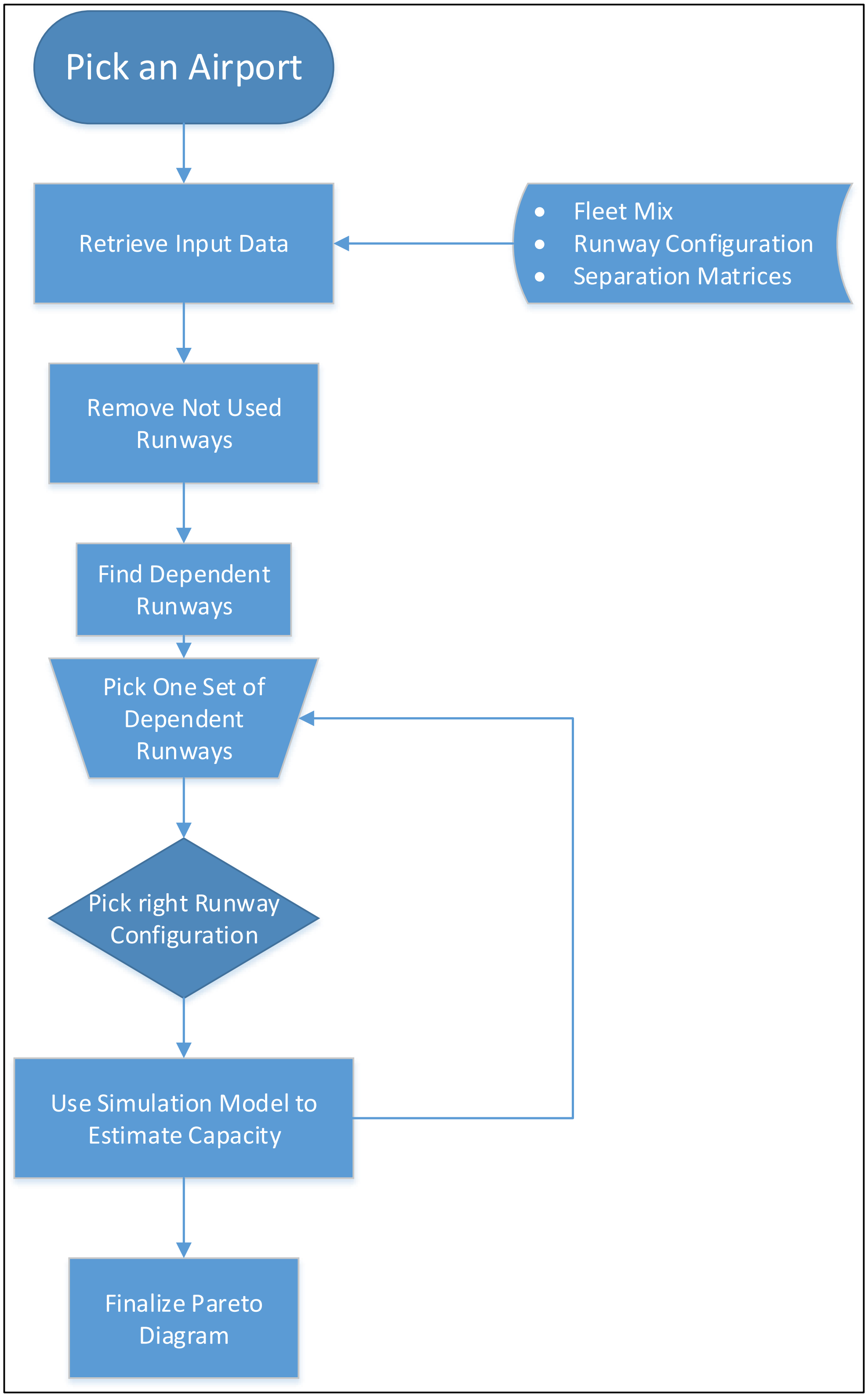


Figure 8. Steps for running one airport.

Capacity estimation for single runway

To estimate the capacity for a single runway, the model estimates several point in the Pareto diagram. The first point is when the airport operates only landings and no departures.

First, the model estimates the information of the first arrival to the entry gate and to the runway. Second, the headway of successive arrivals is calculated by using the minimum runway length separations specified by the FAA or the user. The actual headway takes into account a position buffer error that represents an in-trail delivery error by the controller and caused by pilot flight path uncertainty. The headway between all aircrafts created in the simulation is calculated and the capacity is therefore estimated analytically by using Eq. 1.

$$capacity = \frac{1}{E(headway)} \tag{1}$$

Figure 9 shows graphically how the model calculates the capacity when the airport runs only arrival operations.

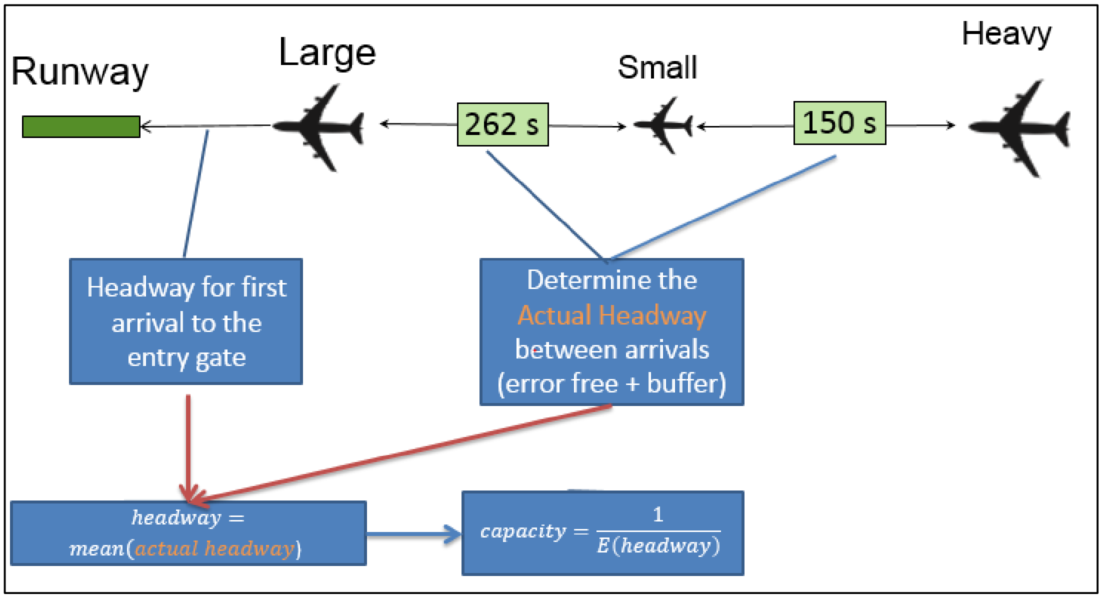


Figure 9. Single Runway – 100% Arrival Priority.

After estimating the capacity for 100% arrivals, the model calculates the Pareto point when the airport operates only departures and no arrivals. First, the model estimates the information of the first departure at the runway threshold. Second, the position and times of successive departures is calculated using the minimum departure-departure separations specified by the FAA or the user. The headway between all departures created in the simulation is calculated and the capacity is therefore estimated analytically by using Eq. 1. Figure 10 shows graphically how the model calculates the capacity when the airport runs only departure operations.

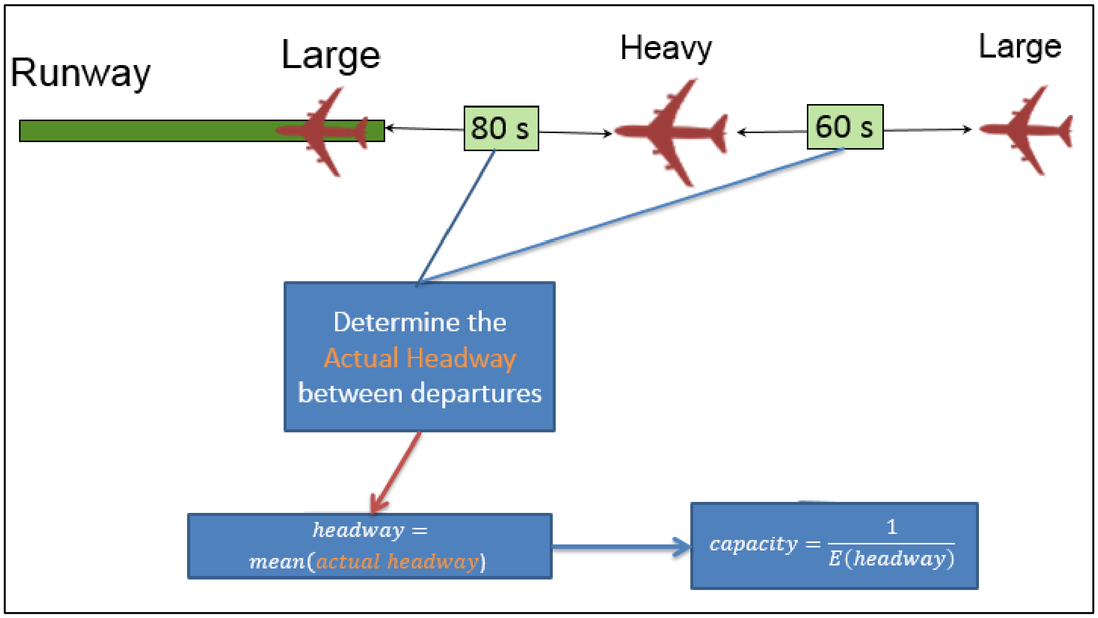


Figure 10. Single Runway – 100% Departures Priority.

Another point that the model estimates is when the control tower gives 100% priority to arrival operations and allows departures within the gaps left between landings. In this case, the capacity of arrivals is calculated the same way as 100% arrival priority. Departures are fit in the gaps left between arrivals (see Figure 11), taking into consideration the minimum separation required between arrivals and departures, which is currently 2nm in the Unites States. If the gap is small, then no departures will be allowed and the same takeoff will be attempted in the next gap between landings. If one departure is allowed between two arrivals, then a second departure will be attempted in the same gap by using the minimum departure-departure separations specified by the FAA or the user. Overall, the headway between all departures created in the simulation is calculated and the capacity is therefore estimated analytically using Eq. 1.

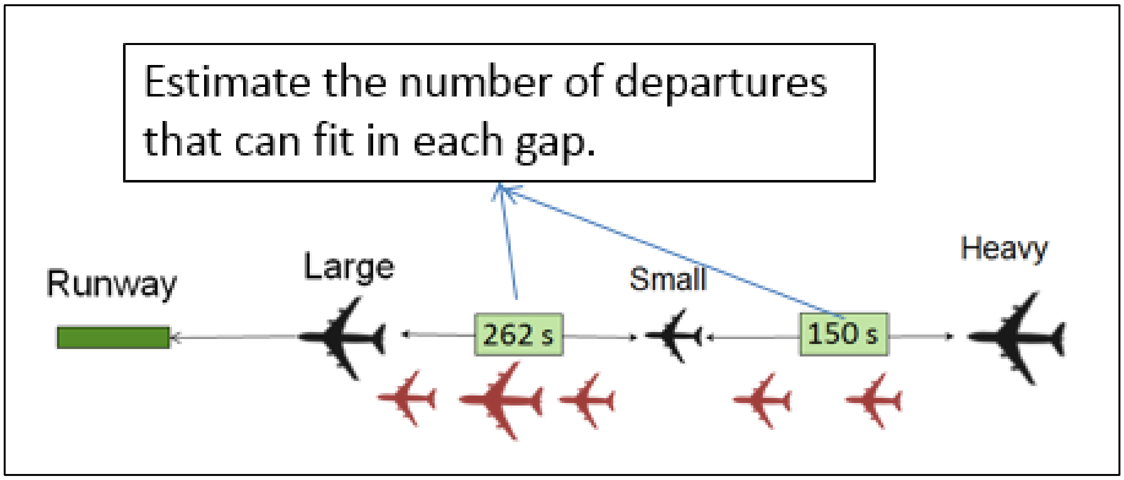
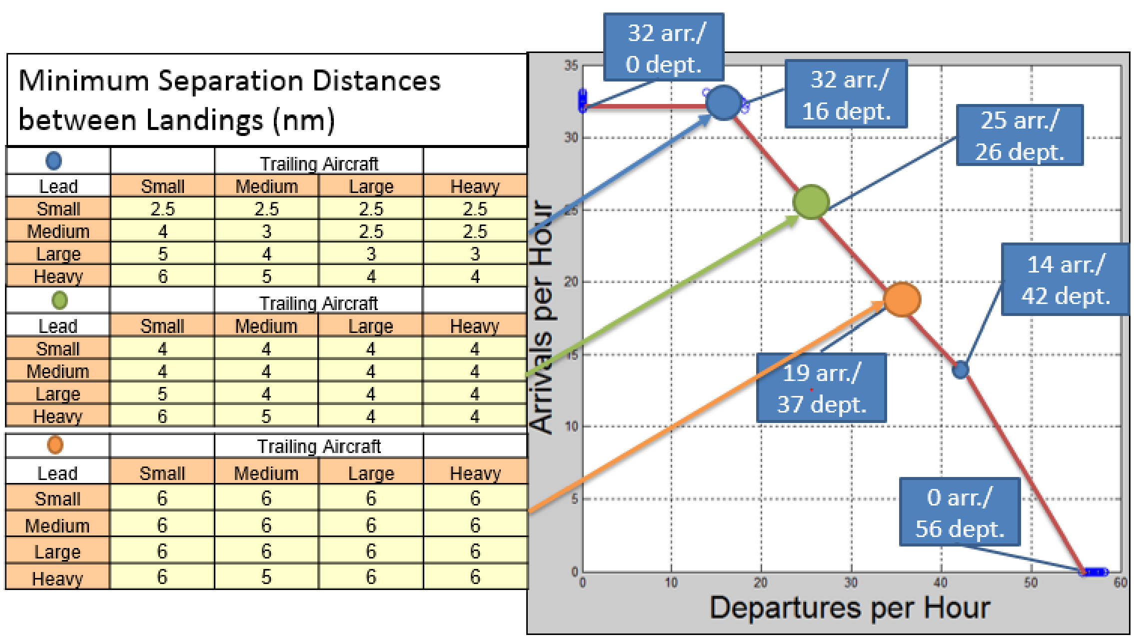


Figure 11. Single Runway – Departures w/ 100% Arrival Priority.

Once we estimate the points representing 100% departures and departures with 100% arrivals, there is a need to calculate more points within these extreme locations to better estimate the Pareto diagram boundaries. In order to estimate these points, we increase the separation between landings so more departures can fit to larger arrival gaps (see Figure 12).



Minimum Separation Distances between Landings (nm)

	Trailing Aircraft			
Lead	Small	Medium	Large	Heavy
Small	2.5	2.5	2.5	2.5
Medium	4	3	2.5	2.5
Large	5	4	3	3
Heavy	6	5	4	4

	Trailing Aircraft			
Lead	Small	Medium	Large	Heavy
Small	4	4	4	4
Medium	4	4	4	4
Large	5	4	4	4
Heavy	6	5	4	4

	Trailing Aircraft			
Lead	Small	Medium	Large	Heavy
Small	6	6	6	6
Medium	6	6	6	6
Large	6	6	6	6
Heavy	6	5	6	6

Figure 12. Other Points in Pareto Diagram.

Capacity Estimation for Multiple Runways

Using the same procedures to create Pareto boundaries for a single runway, the model estimates several point in the Pareto diagram for multiple runways: two intersecting, two parallel runways, three runways and four runways.

Intersecting Runways

The first point in the Pareto boundary corresponds to the airport operated with landings only. In this case, we assume that both intersecting runways operate landings. First, we identify a primary runway and the information of a first arrival stream is estimated using the method for a single runway. The arrivals on the secondary runway are then estimated by fitting discrete arrivals in the gaps left between successive landings on the primary runway. For example, an arrival on the secondary runway can be allowed after the arrival on the primary runway has crossed the intersection between either runways or when the arrival on the primary runways has left the runway. In addition, when the arrival of the secondary runway crosses the intersection or leaves the runway, the next arrival on the primary runway has to be at a minimum separation distance (see Figure 13). If one landing on the secondary runway is possible, then a second landing on the same runway is attempted by observing the minimum separation requirements for consecutive arrivals on the secondary runway.

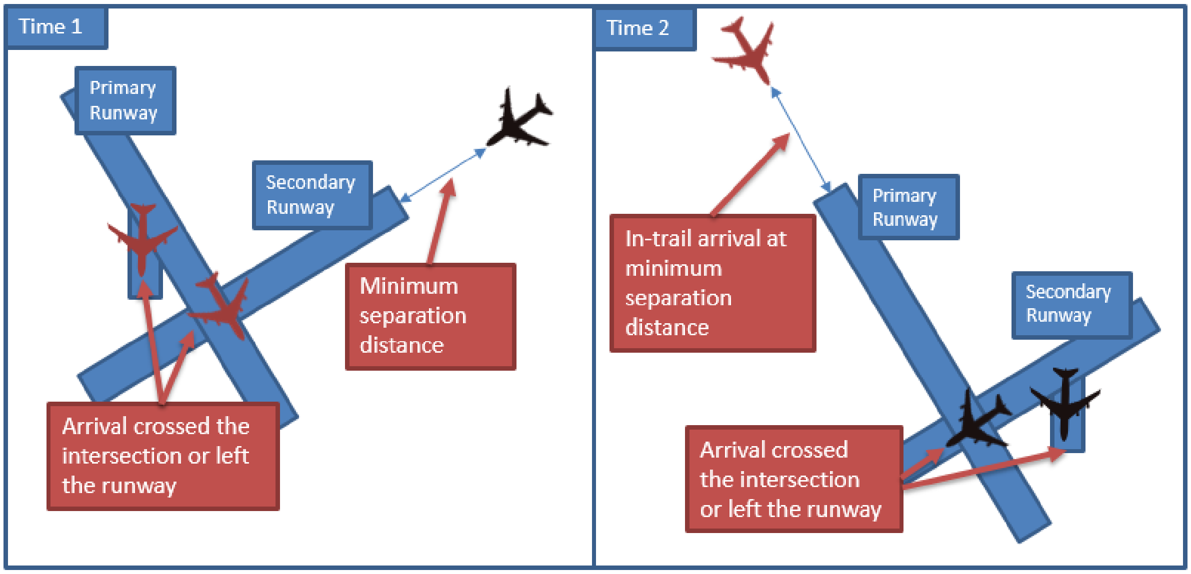


Figure 13. Arrival on Secondary Runway.

After estimating the capacity for 100% arrivals, the model calculates the Pareto point when the airport operates only departures and no arrivals. A primary runway is identified and the information of a first departure stream is estimated using the same principles employed for a single runway. The departures on the secondary runway are then estimated by fitting departures in the gaps left between departures on the primary runway. A departure on the secondary runway can be allowed after the departure on the primary runway has crossed the intersection between both runways. If the departure on the first runway is airborne by the time it reaches the intersection, a departure on the secondary runway has to follow the minimum wake separations between departures on the same runway, thus it cannot take off right after the first departure has crossed the intersection. If one takeoff is possible on the secondary runway, then a second departure on the same runway is attempted by observing the minimum separation requirements for consecutive departures on the same runway.

Another point that the model estimates is when the air traffic assigns 100% priority to arrival operations and allows departures within the gaps left between landings. In this case, the two intersecting runways are both operated in mix mode with arrivals and departures. All the rules explained in previous paragraphs are combined to estimate the headway between operations. First, a primary runway is identified and the information of a first arrival stream is estimated following similar rules to those of a single runway. If the secondary runway also operates arrivals, then landings on the intersecting runway are filled into the gaps left between arrivals on the primary runway. After exhausting all possible landings, takeoffs are attempted within the gaps left between arrivals using the same principles used for a single runway. This is illustrated in Figure 14.

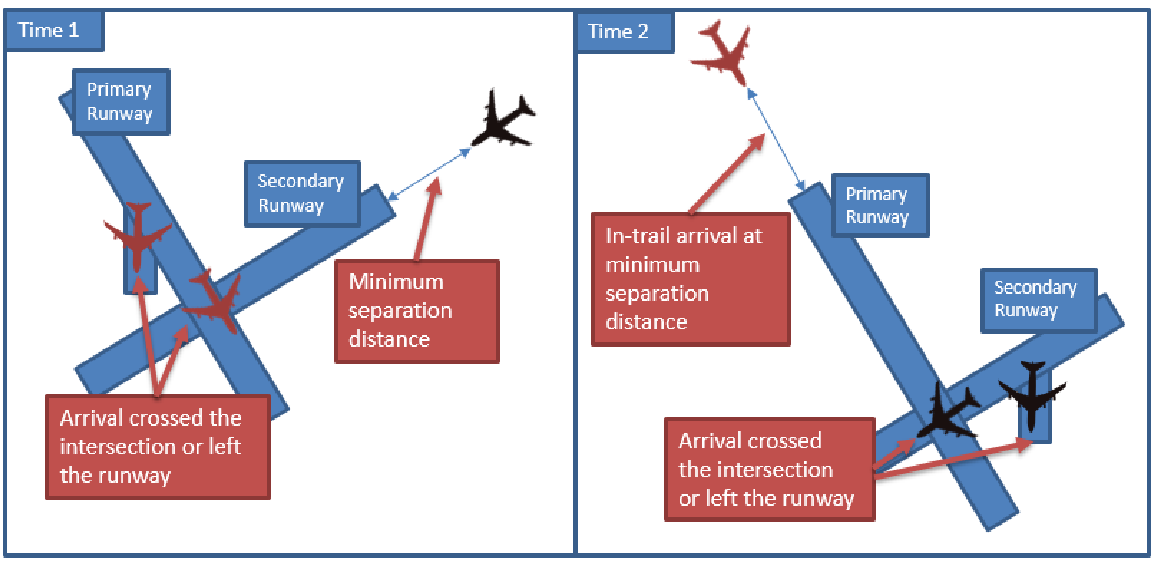


Figure 14. Departure on Secondary Runway.

Non-intersecting converging runway operations

Some runways do not physically intersect but their extended paths do, which can lead to non-intersecting converging runway operations under certain scenarios. For instance, an arrival stream that intersects the arrival path of another runway (see Figure 15.A) or a departure stream that crosses the path of another runway once it leaves its own runway (see Figure 15.B). In addition, even if a landing does not cross the path of another runway, operations are dependent from each other considering the 1nm distance rule in the FAA new procedures (JO7110.652). For such operations, calculations of runway capacity are similar to two intersecting runways. The model estimates the times at which landings and departures cross the converging path points before and after they use the runway.

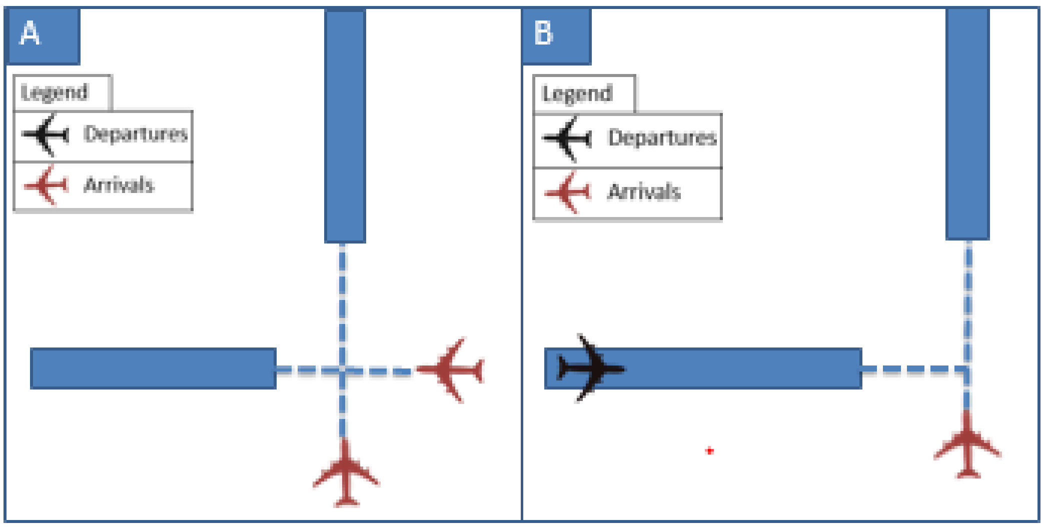


Figure 15. Non-Intersecting Converging Runways.

Parallel Runways

Similarly to the previous cases, the first point estimated is when the airport operates only landings and no departures. In the case of two parallel runways, the distance between the two parallel runway's centerline must be known to establish whether two runways are dependent from each other. According to current FAA regulations, under IMC conditions if two parallel runways are spaced less than 2,500 feet then arrivals are dependent from each other and they follow the close parallel 1.5nm diagonal rule[12] (see Figure 16.A). On the other hand, if parallel runways are spaced between 2,500 feet and 4,300 feet, the 1.5nm diagonal rule in the FAA JO 7110.65U[13] is used (Figure 16.B). If the two parallel runways are spaced more than 4,300 feet then the two runways are independent from each other and the capacity of the two runways is calculated as two single runways. Under VMC conditions, according to current FAA regulations (AC 150/5300-13A), if two parallel runways are spaced more than 700 feet than simultaneous landings can be allowed.

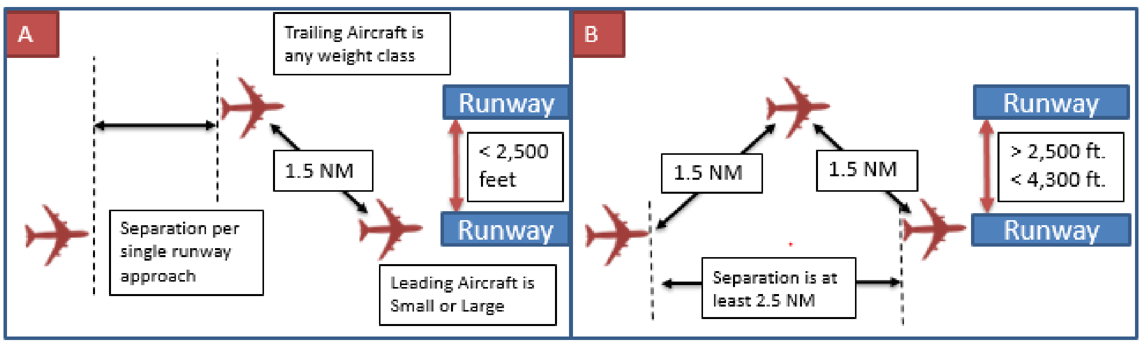


Figure 16. Close Parallel Landing Rule.

After estimating the capacity for 100% arrivals, the model calculates the Pareto point when the airport operates only departures and no arrivals. In the case of two parallel runways, the distance between the parallel runways is needed to establish whether two runways are dependent from each other. Under radar conditions, according to current

[12] "NM Dependent Approaches to Parallel Runways Spaced Less than 2500 Ft Apart." November 1, 2008. Accessed November 8, 2014. http://www.faa.gov/documentLibrary/media/Order/JO 7110.308.pdf.

[13] "Air Traffic Control." April 1, 2014. Accessed November 8, 2014. https://www.faa.gov/documentLibrary/media/Order/ATC.pdf.

FAA regulations[14], if two parallel runways are spaced more than 2500 feet simultaneous takeoff can be allowed. On the other hand, under VMC conditions, 700 feet of separation between runway's centerlines is needed to allow independent departures.

Another point in the Pareto boundary that the model estimates is when the control tower assigns 100% priority to arrival operations and allows departures within the gaps left between landings. In the case when two parallel runways operate both arrivals and departures, all the rules explained in previous paragraphs are combined to estimate the headway between operations. The benefit of using two runways is achieved by the fact that a departure can be released as soon as an arrival has crossed the runway threshold of the other runway and it does not have to wait until the arrival has left the runway.

Staggered Parallel Runways

The model is able to estimate the time at the threshold when two parallel runways are staggered from each other. The stagger is important to establish whether simultaneous approaches and takeoffs can be allowed on two parallel runways and to enforce the 1.5nm diagonal rule. Runway stagger can be positive or negative, according to how the operations are operated on each runway. Two parallel runways are positively staggered if the landing aircraft is to the runway with the threshold closer and negative if the landing is to the far threshold (see Figure 17).

[14] "150/5300-13A - Airport Design." Federal Aviation Administration. September 1, 2012. Accessed November 8, 2014. http://www.faa.gov/documentLibrary/media/Advisory_Circular/150-5300-13A-chg1-interactive.pdf.

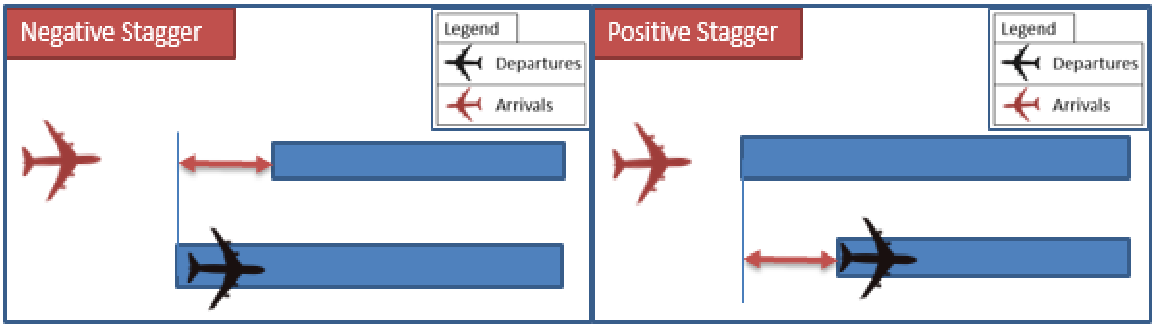


Figure 17. Positive and Negative Stagger.

Two Parallel and one Intersecting runways

All the rules explained before for two parallel runways and two interesting runways are combined and applied to the three-runway case. All possible scenarios with different arrivals and departures on three runways are considered.

Four runways

In this model, the capacity for an airport with four dependent runways is only limited to the case when the airport operates no more than three runways for arrivals and no more than three runways for departures. In addition, if the airport operates three runways for arrivals and departures operations have to be on two parallel runways and one intersecting runway. A possible scenario for four dependent runways is given by the most used runway configuration for Philadelphia International airport (PHL) under IMC conditions in 2013 (see Figure 18). In this case, all four runways are dependent from each other and the airport operates landing on runways 09R and 17 and departures from runways 09L and 08.

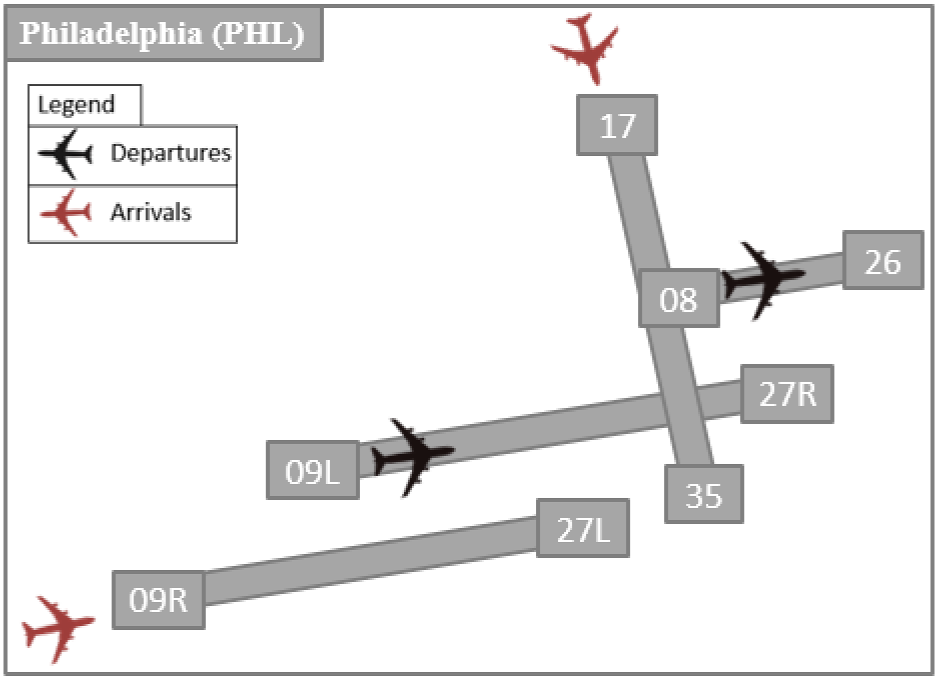


Figure 18. Four Dependent Runways – PHL.

Minimum Runway Length

Some runways might be too short to safely operate certain types of aircraft. In order to take into account this limiting factor, the model carries out an aircraft type check for each operation simulated. If the aircraft type requires more runway length to safely land or takeoff at a specific runway, the model does not allow the operation on that runway and attempts to operate that aircraft on a different runway. The minimum runway lengths requirement for each category of aircraft were found through a study on the minimum runway lengths for takeoff and landing for each aircraft in the Eurocontrol BADA 3.11 list. The minimum runway lengths are also adjusted for the airport elevation through regression analysis.

Controlling Error

The number of aircraft generated in each ordered list is generally high, in order to obtain an unbiased saturation capacity with low error. In addition, for each simulation case the user can define a finite number of runs so the bias error is controlled.

The goal of our simulation is to find an unbiased mean for the headway between aircraft (θ). This estimator is found across n replications of the unbiased estimator ($\widehat{\theta_j}$) for the mean from the jth i.i.d. replications, which is defined to be $\bar{\theta}(n) = \frac{1}{n}\sum_{j=1}^{n} \widehat{\theta_J}$. Equation 2 shows the normal-theory (1-a) 100% confidence interval for the mean when n is a fixed number of replications.

$$\bar{\theta}(n) \mp t_{1-\frac{a}{2},n-1} \frac{S(n)}{\sqrt{n}} \quad (2)$$

In order to reduce the variance of the replication estimators, we take a large number of aircraft so we reduce the error bound.

3.2.4. Graphical User Interface (GUI)[15]

This model comes as standalone software with its own graphical user interface (GUI) built using Visual Studio Pro 2012 to simplify user experience. The GUI provides a default value for each parameter in the model that the user can decide to modify in order to predict capacity for scenarios with improved technology, different airport information, minimum separation rules and scenario refinement. Figure 19 shows the main window of the model where the user selects the airport ID, weather condition, aircraft grouping system, output file names and can get access to the other windows of the model.

[15] In collaboration with Nicolas Hinze (ATSL lab) in the development of the GUI

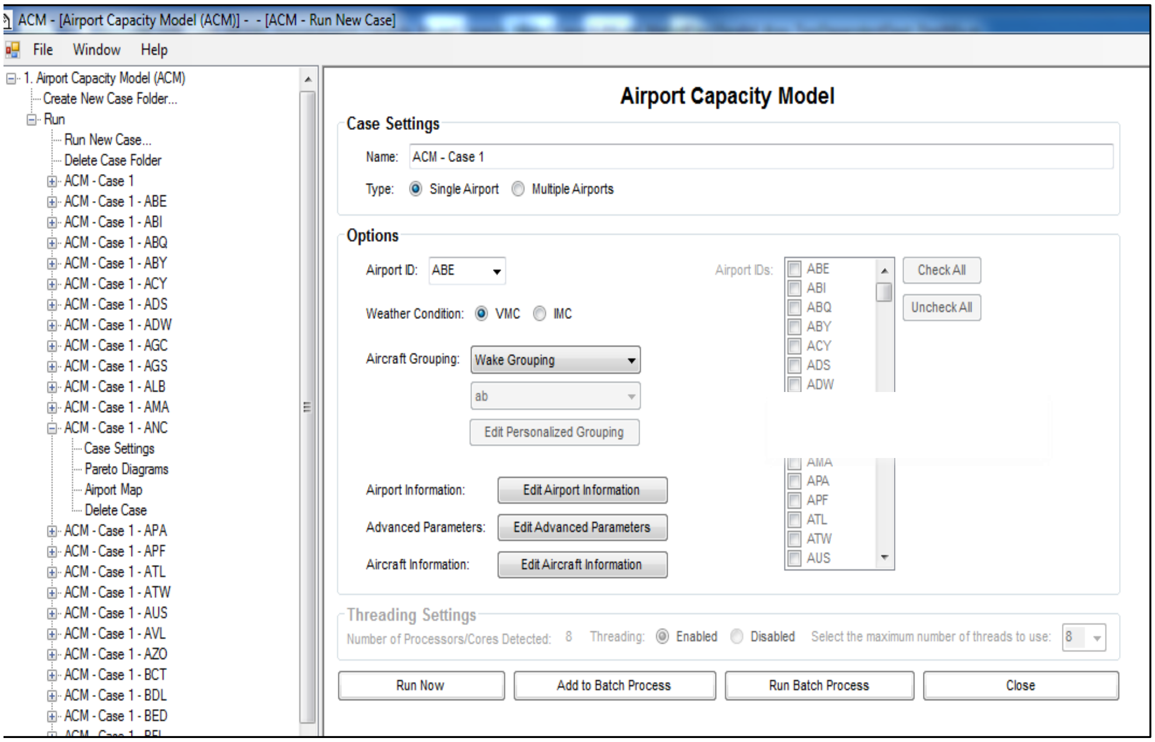


Figure 19. Graphic User Interface – Main Page.

Since this model is expected to run future airport scenarios, the model is prepared to run any number of groups of aircraft. Each group represents aircraft with similar characteristics. In the Personalized Aircraft Grouping window (Figure 20), the user defined its own aircraft grouping system. The parameters required are number of groups, group name, and type of aircraft that belong to each group. Maximum takeoff weight and aircraft wingspan are the two factors used to assign an aircraft to a specific group.

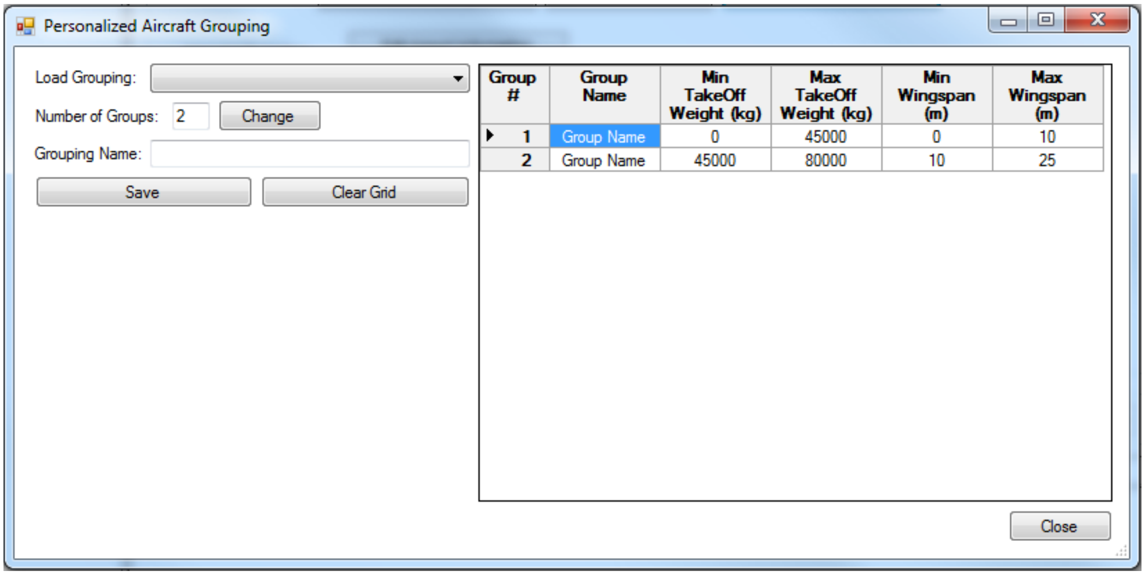


Figure 20. Graphic User Interface – Personalized Aircraft Grouping Windows.

In the Airport Information window, the user can modify the parameters specific to the airport chosen: airport elevation, fleet mix, runway configuration and the presence of a control tower. In addition, this page also provides a graph with the runway orientation and how arrivals and departures are operated at the airport (see Figure 21)

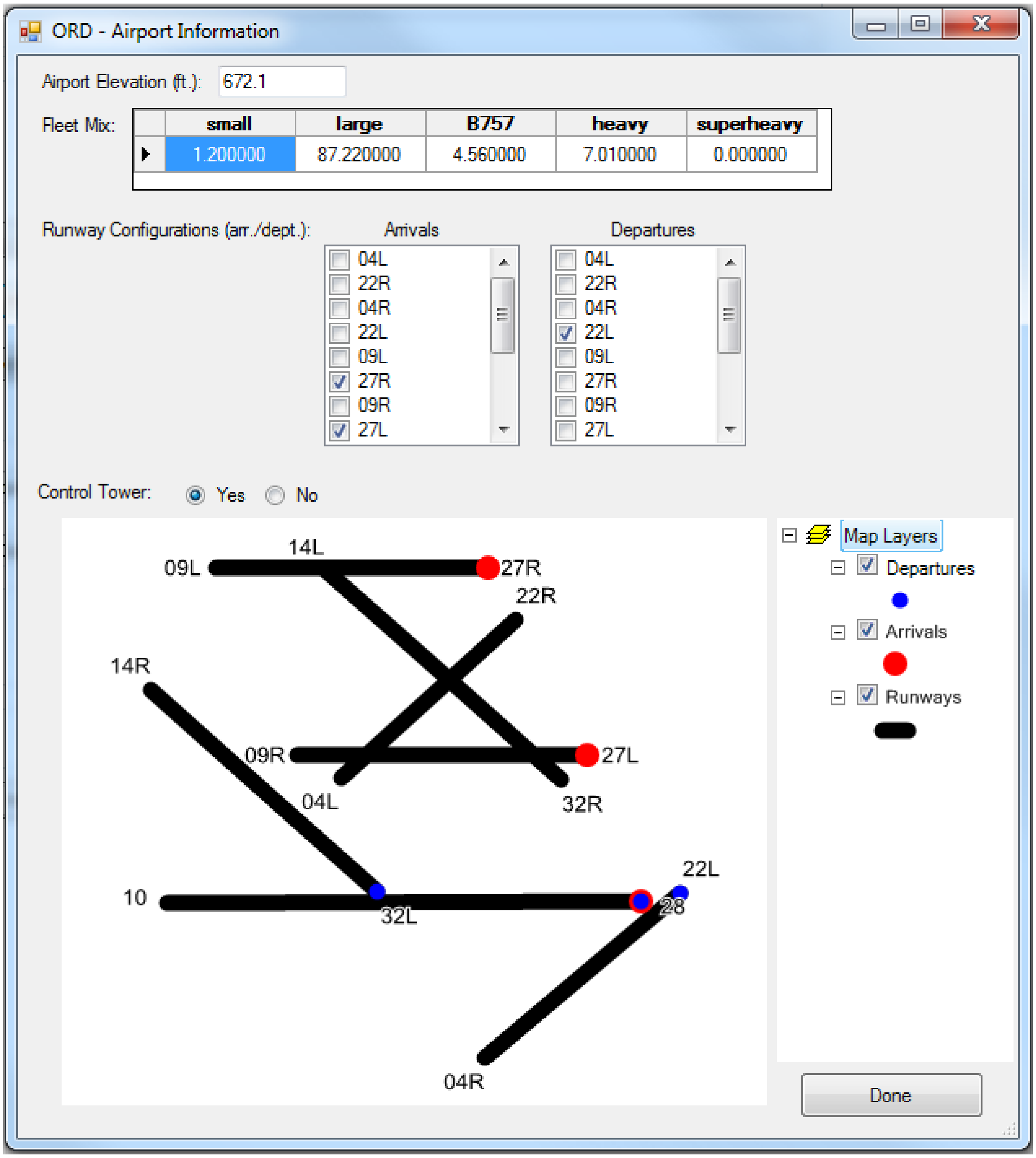
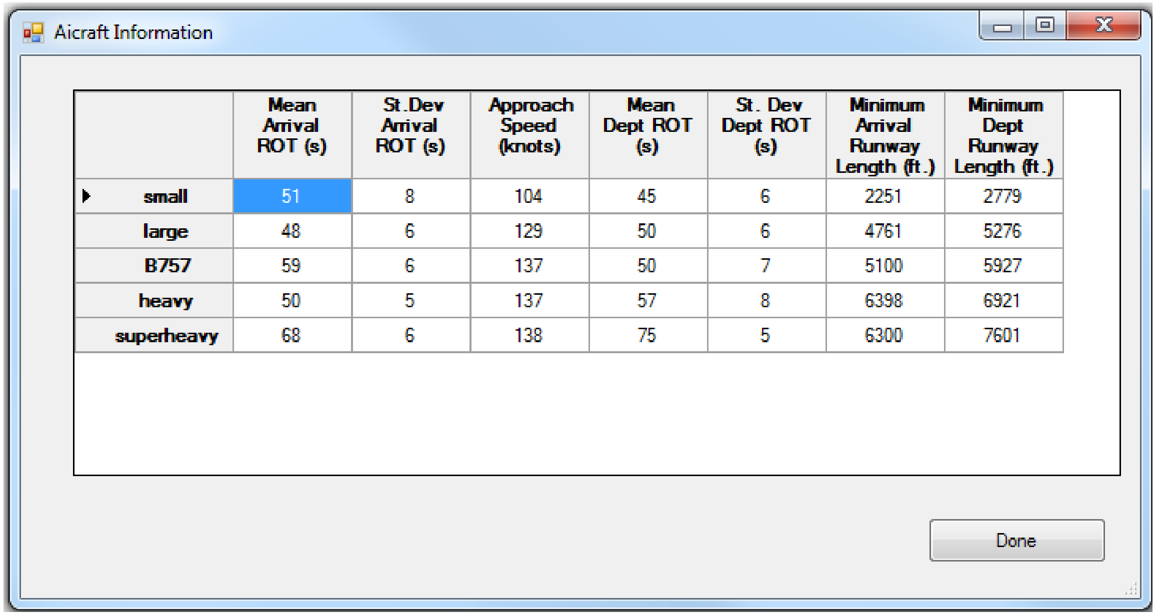


Figure 21. Graphic User Interface – Airport Information Window.

In the Aircraft Information window, the user can modify all parameters specific to each group of the aircraft grouping system chosen: ROTs, approach speed and minimum runway length. (See Figure 22)



	Mean Arrival ROT (s)	St.Dev Arrival ROT (s)	Approach Speed (knots)	Mean Dept ROT (s)	St. Dev Dept ROT (s)	Minimum Arrival Runway Length (ft.)	Minimum Dept Runway Length (ft.)
small	51	8	104	45	6	2251	2779
large	48	6	129	50	6	4761	5276
B757	59	6	137	50	7	5100	5927
heavy	50	5	137	57	8	6398	6921
superheavy	68	6	138	75	5	6300	7601

Figure 22. Graphic User Interface – Aircraft Information Window.

The advanced parameter window allows the user to modify all other input values of the model. This includes ATC minimum separation distances and refinement of the run. (See Figure 23) A user can also define different parameters for global runway distance parameters and ATC-pilot time lags.

In this window, it is possible to select the refinement level of the scenario run. The number of random flights simulates should be a large number to control the bias. Each scenario can also be run multiple times to further reduce the error. The refinement level indicates the number of Pareto points that the model will generate to have more accurate Pareto boundaries.

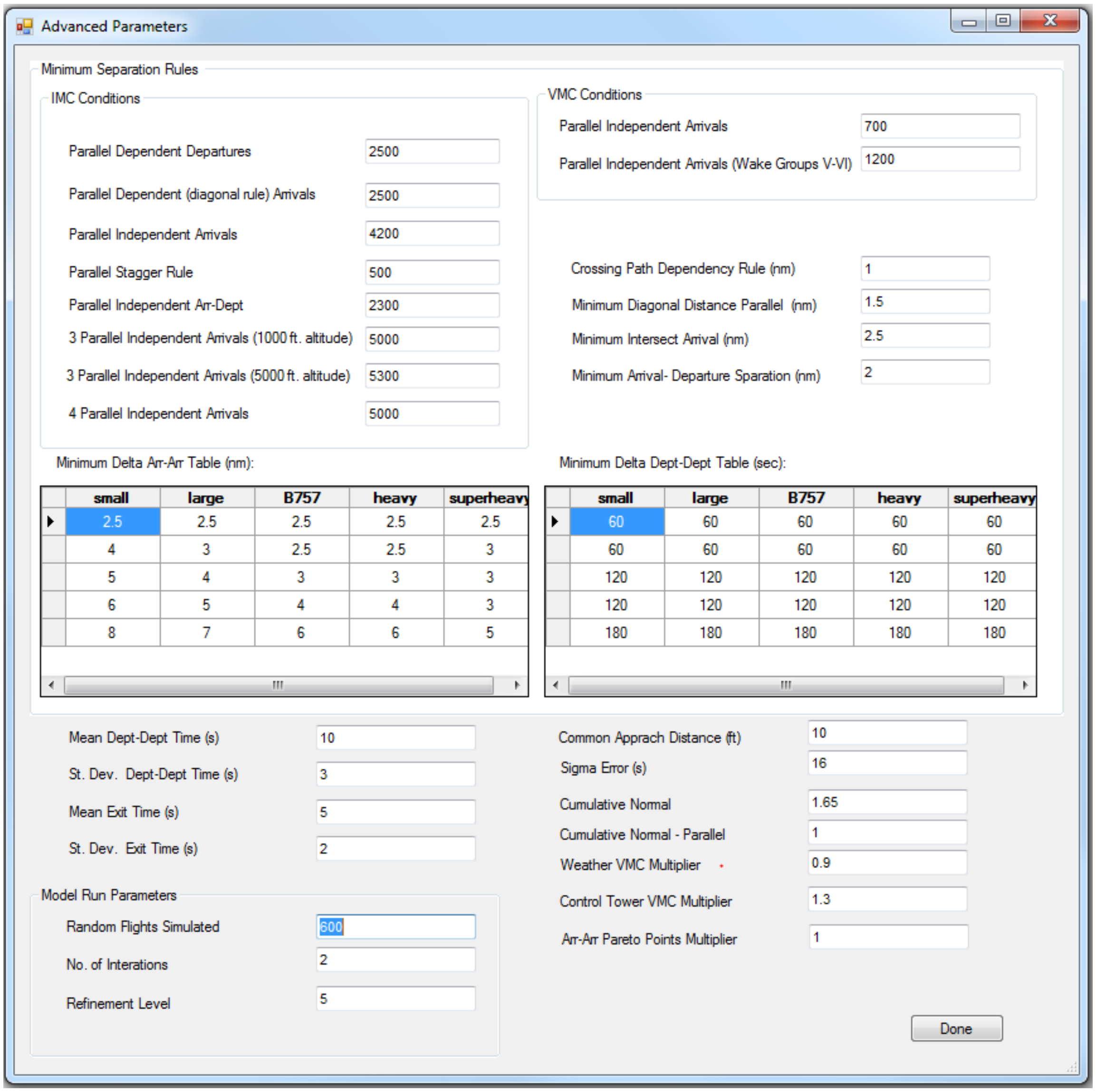


Figure 23. Advanced Parameters.

3.2.5. Validation

In this chapter, we validate the model developed using the runway throughput capacity calculated by the model and compare it with FAA ASPM data. We also look into the change in runway capacity when various airport inputs are varied.

Effective Throughputs

To verify the model outputs we plot the Pareto diagrams against the observed hourly throughputs in the FAA ASPM data for the top 77 airports in the NAS.

To illustrate the point, consider San Diego International Airport (SAN) with one runway. According to ASPM data the most used runway configuration in 2013 according to ASPM data was runway 27 in mixed mode. Figure 24 shows that 99.9% of the collected observations are within the Pareto boundaries.

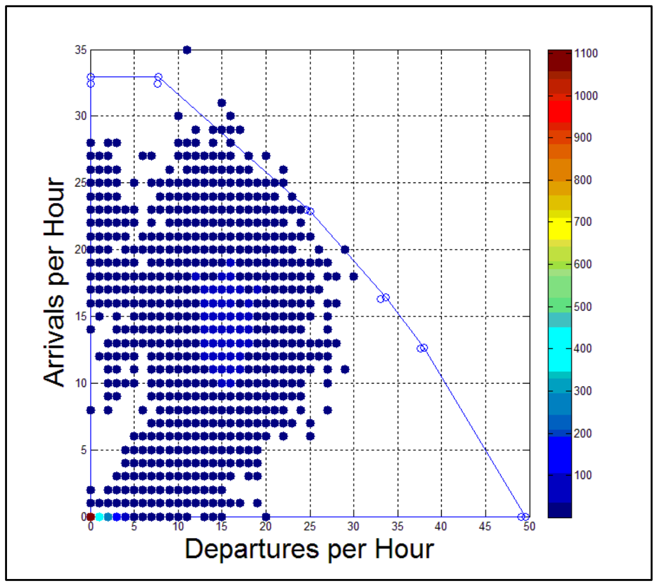


Figure 24. San Diego International Airport (SAN).

The FAA has introduced early this year (2014) a new rule for converging runway operations[16]:

"If the extended centerline of a runway crosses a converging runway or the extended centerline of a converging runway within 1NM of either departure end, apply the provisions of paragraph 3-9-8, Intersecting Runway Separation."

[16] FAA JO 7110.652

This rule has a great impact on the capacity of many airports. Figure 25 shows how the Pareto diagram for Minneapolis Saint-Paul (MSP) with and without the new FAA regulation, We observed that when implementing the new FAA rule many observations of the effective arrival-departure operations are outside the diagram. On the other side, when the new FAA rule is not enforced in the model, 100% of the APM observations are within the Pareto boundaries. Both Pareto diagrams are estimated using the most used runway configuration for MSP in 2013, which includes arrivals on runways 35, 30L and 30R and departures on runways 30L and 30R. The effective arrivals and departures operations points scattered in the two graphs are those associated with the same runway configuration declared by the airport.

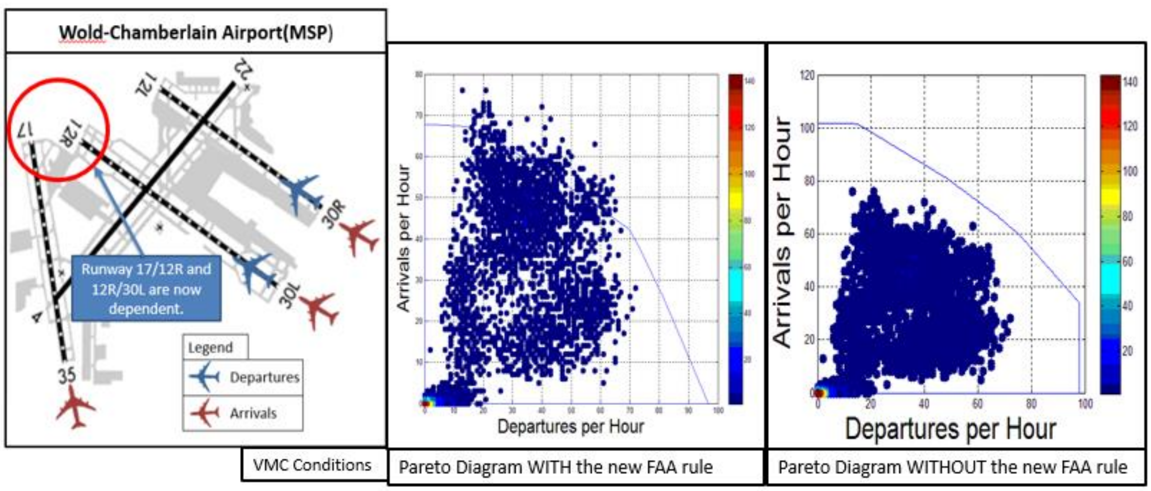


Figure 25. Minneapolis- Saint Paul International Airport – Pareto Diagrams Compare.

The same trends can be found in the two Pareto diagrams shown for Boston Logan International airport (BOS) in Figure 26. With two departures and arrivals streams, the new FAA rule creates a runway dependency between runways 9/27 and 4L/22R, which reduces the capacity of the airport.

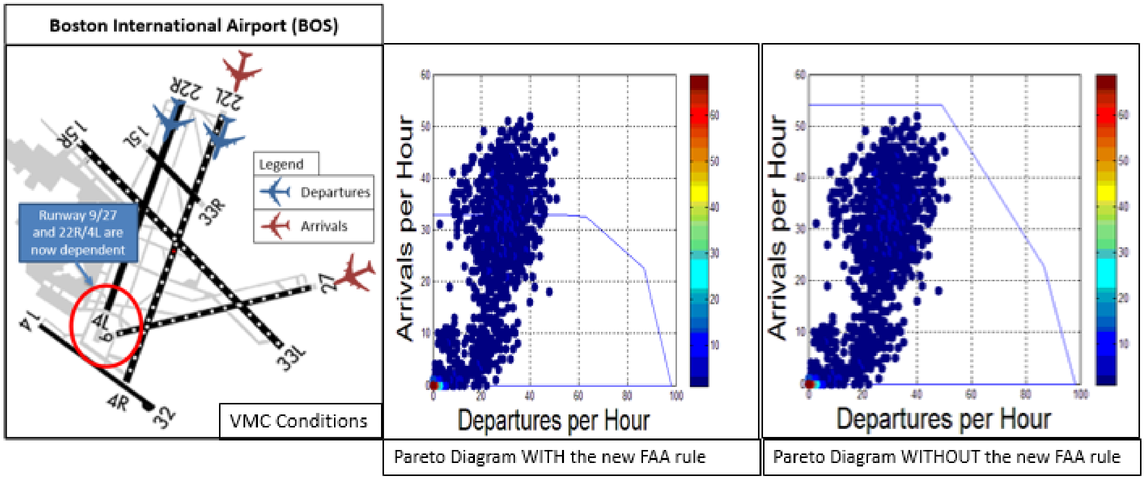


Figure 26. Boston Logan International Airport – Pareto Diagrams Compare.

An interesting result can be seen for Ronald Reagan airport (DCA), shown in the top Figure 27. The most used runway configuration declared by the airport is to use runway 01 in mixed mode but only 60% of the observations are within the Pareto diagram. Nevertheless, the declared runway configuration for DCA seems unrealistic because a single runway cannot operate 35+ arrivals and 30+ departures in an hour. We believe that very likely the airport was operating two runways to support some of the points outside our estimated Pareto diagram. In fact, we run our model again including landings on runway 33 and the new Pareto boundaries shown in the bottom Figure 27 include now most of the throughputs points declared by the airport.

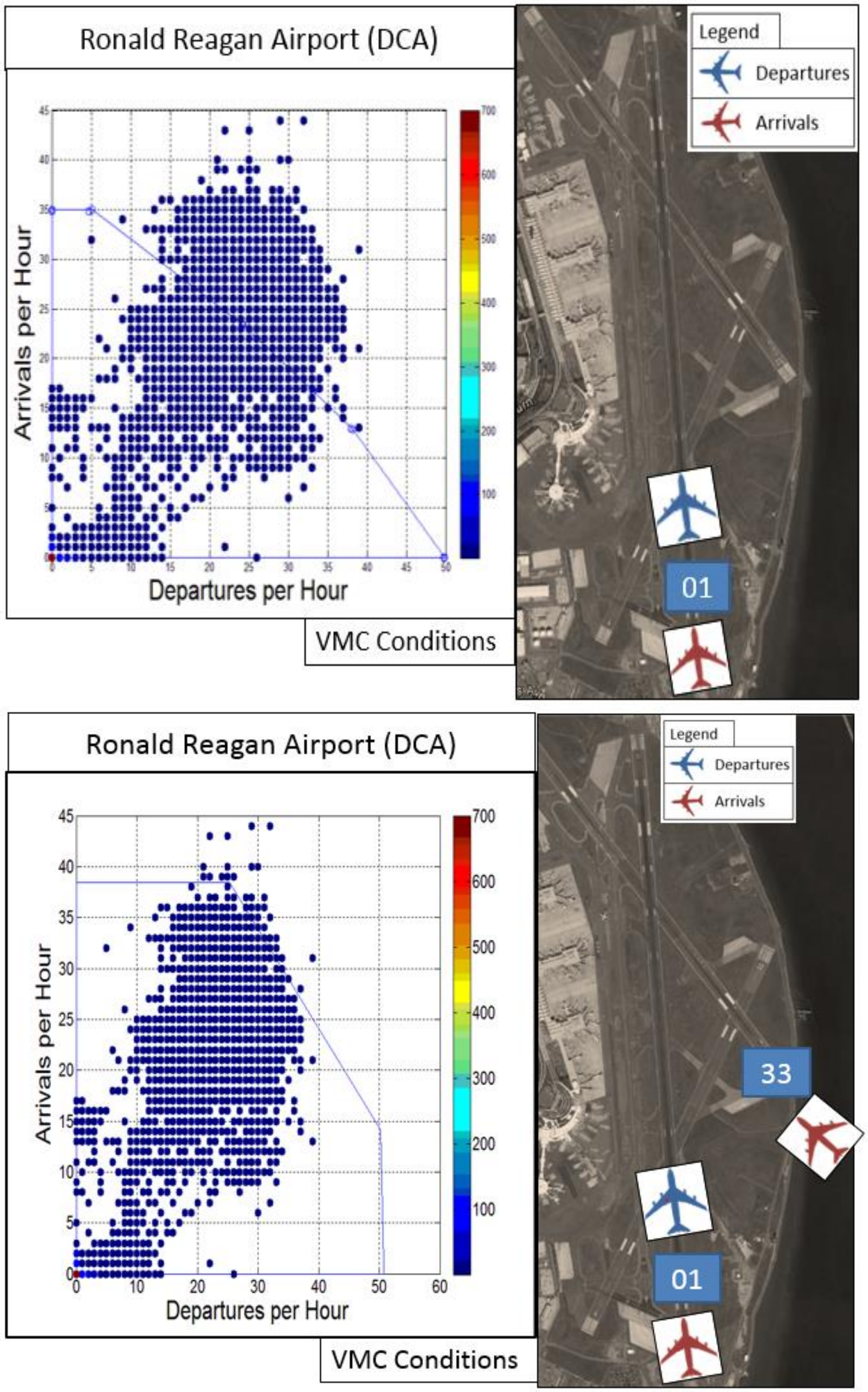


Figure 27. Ronald Reagan Airport (DCA) – Pareto Diagrams Compare.

In the case of two parallel runways such as Los Angeles International airport (LAX), the Pareto diagrams (Figure 28) generated by this model included 92% of the ASPM observations under IMC conditions and 88% of the points under VMC conditions. We believe that the points outside the Pareto diagram can be explained by the fact that very likely in those hours LAX was operating with a different fleet-mix, probably less heavy and super heavy aircraft. The airport might also have operating more homogeneous fleet mix across the four runways. In these cases, the airport could operate with less separation between successive arrivals and therefore allow more landings per unit of time.

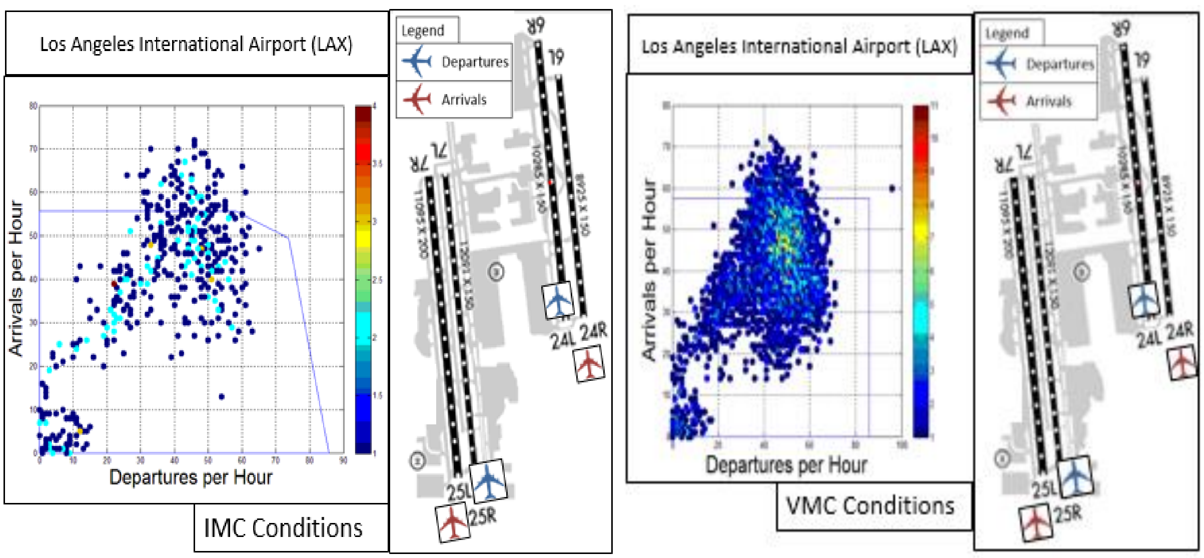
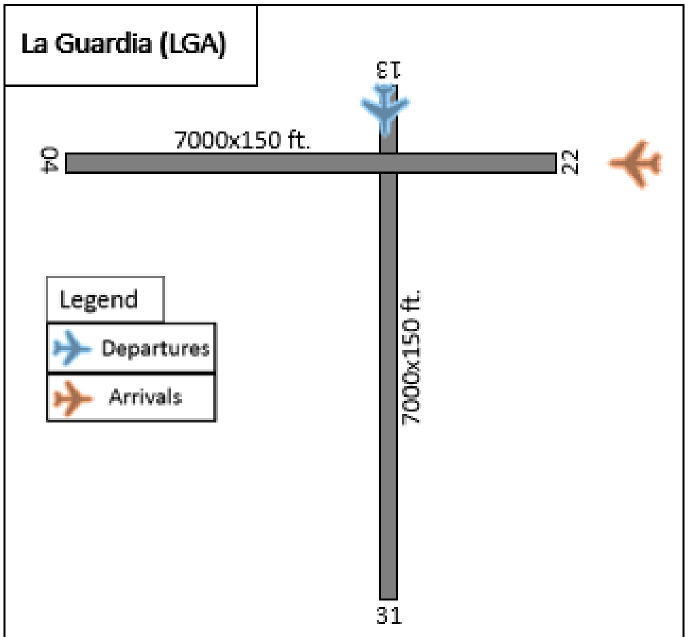


Figure 28. Los Angeles International Airport (LAX) – Pareto Diagrams Compare.

Validation of Individual Airport Trends

Another form of model validation is to study the change in runway capacity when airport operational changes occur. For instance, we investigate changes to capacity if we modify the intersection point of two runways. The fleet mix or the separation rules but maintaining fixed all other factors. The base airport for our validation is LaGuardia

International Airport (LGA) with its two intersecting runways 04/22 and 13/31, as shown in Figure 29. Landings occur on runway 22 while departures are operated on runway 13. The fleet mix for the airport can be found at the bottom of Figure 27.



Small	Large	B757	Heavy	Super Heavy
8	88	4	0	0

Figure 29. Validation Base Scenario – Intersecting Runways.

First, we observed the change in capacity for two intersecting runways when the intersecting point of the two runways is shifted further and further away from the two runway ends that operate arrivals (22) and departures (13). As expected, the capacity of the airport increases as long as the aircraft have to wait less before they are released or being at a longer distance from the threshold. Figure 30 shows different Pareto diagrams representing variations of the intersection point. Case A depicts the scenario where the two runway ends (22 and 13) overlap. In this case, arrival and departure streams can be serviced, as they are nearly independent from each other.

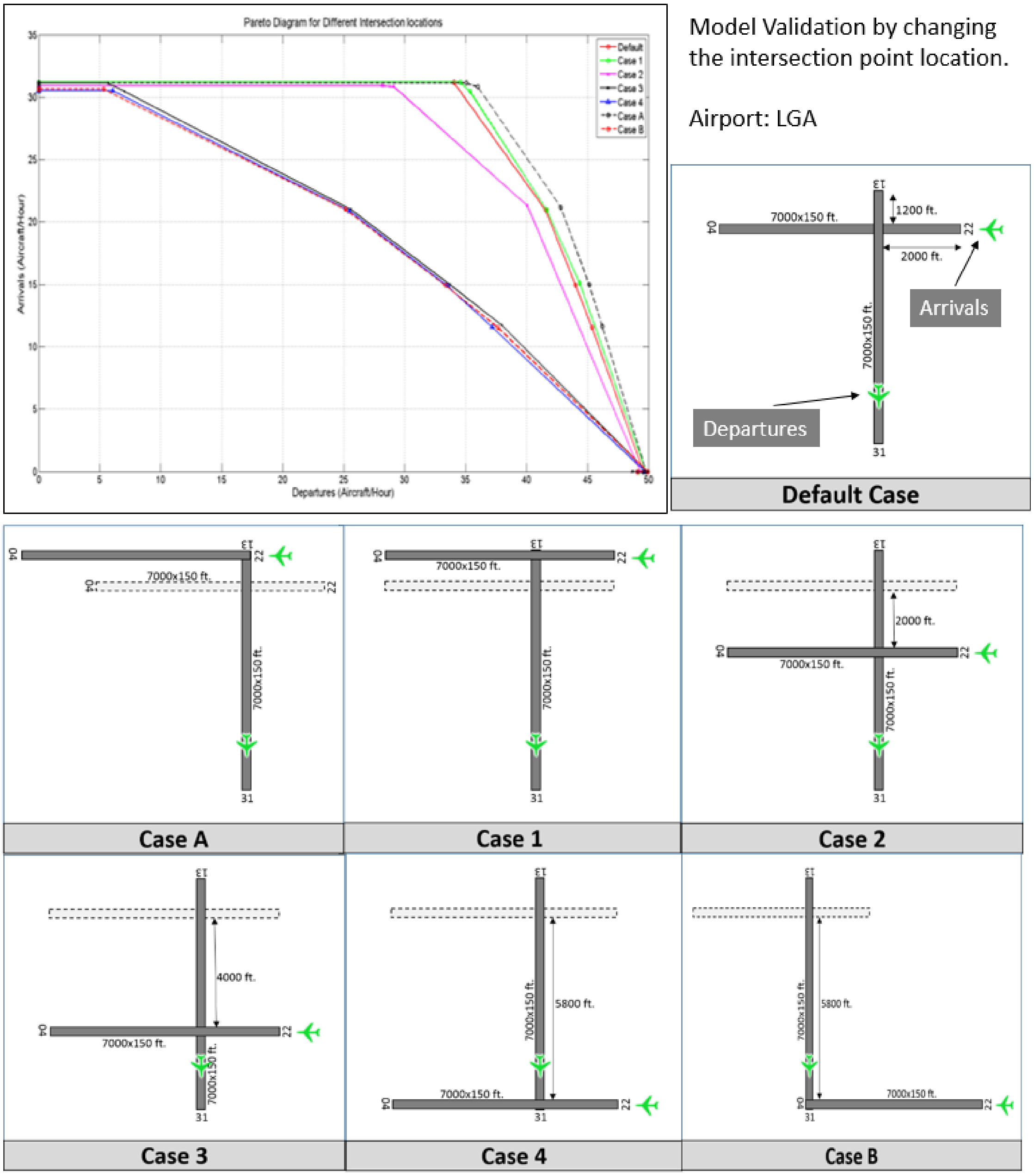


Figure 30. Model Validation by Changing the Intersection Point Location.

Another form of trends studied is changing the percentage of aircraft types that operate at the airport. For this validation the legacy wake groups were used. We first run a heterogeneous case with twenty percent of the feet mix assigned to each aircraft group. Then, we studied heterogeneous cases with 100% for each single wake class. The resulting Pareto diagrams are shown in Figure 31, which show that the current fleet mix at LGA does not provide maximum throughput. Looking at Figure 31 we identify trends that might seem counterintuitive at first:

- The scenario with most arrivals at LGA is operating 100% large aircraft; this is because large aircraft types have lower minimum arrival-arrival separation distance. The same separation distance applies to small aircraft but the approach speed for small aircraft is lower than the large type, thus resulting in lower throughput capacity. Therefore, with the same common approach distance for both groups, large aircraft type takes shorter times to reach the runway threshold.
- The scenario with most departures at LGA operating 100% small aircraft and this is expected since this aircraft group has the lowest minimum departure-departure separation.
- For the two scenarios with 100% heavy and super-heavy aircraft, the two Pareto diagrams form almost a rectangular boundary. This means that are arrivals and departures are close to being independent from each other. This is because the large separation distances between successive arrivals allow one departure or more in each arrival gap.
- The scenario with the least number of arrivals at LGA is operating a heterogeneous fleet mix. At first, it could seem counterintuitive that the scenario with 100% super-heavy has more arrivals but the arrival-arrival separation distance between successive super-heavy aircraft is lower than some cases of the heterogeneous fleet mix. In fact, a small aircraft following a heavy or super-heavy

aircraft needs long in-trail distances, which reduces the number of landings allowed in this scenario.

- As expected, the scenario with the least number of departures at LGA is operating 100% super-heavy aircraft.

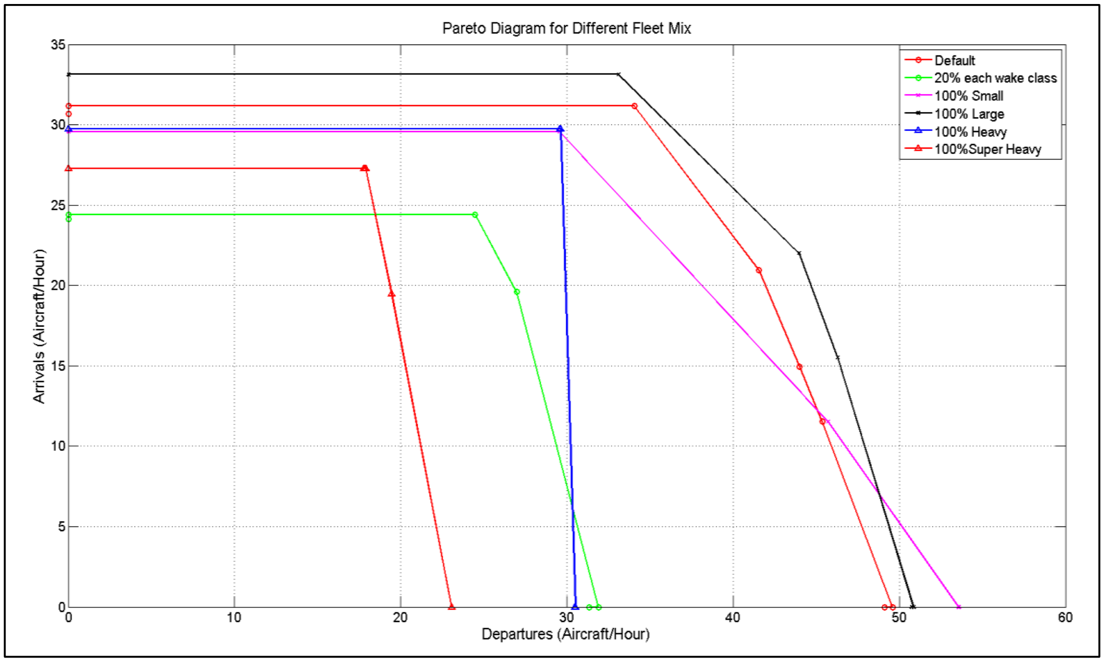


Figure 31. Model Validation by Changing Airport Fleet Mix.

Verification of the Variance and Significance of Estimated Capacity.

The last verification for our model is to estimate the reliability of our results. The calculated Pareto points are validated by providing measures of accuracy, in terms of bias, variance and confidence intervals.

The randomness of the model input variables produces different capacity results for each iteration. In order to simplify the model results, we provide confidence intervals for the variance and mean of predicted arrivals and departures. We tested that each Pareto point estimated comes from a normal distribution using both Anderson-Darling test and Chi-square goodness-of-fit test. Unfortunately, the results of the tests not always rejects the null hypothesis at the 5% significance level that the data does come from such a distribution. To assure the normality of our estimated capacity we used a Bootstrapping statistical method, which consists of constructing a (large) number of random samples with replacement of the observed data. The Central Limit Theory assures that the new dataset follows a normal distribution so the estimated parameters and confidence levels of the Pareto boundaries are known.

Table 23 shows a summary of means, variances and confidence intervals for each point in the Pareto Diagram for a two intersecting runway airport. In one case, the Anderson-Darling test rejected the null hypothesis and bootstrapping was necessary to ensure normality of our dataset. Figure 32 shows the plotted Pareto diagram with the upper and lower Pareto boundaries and the maximum variance for arrivals and departures, which are 3.1 aircraft for arrival operations and 8 aircraft for departures.

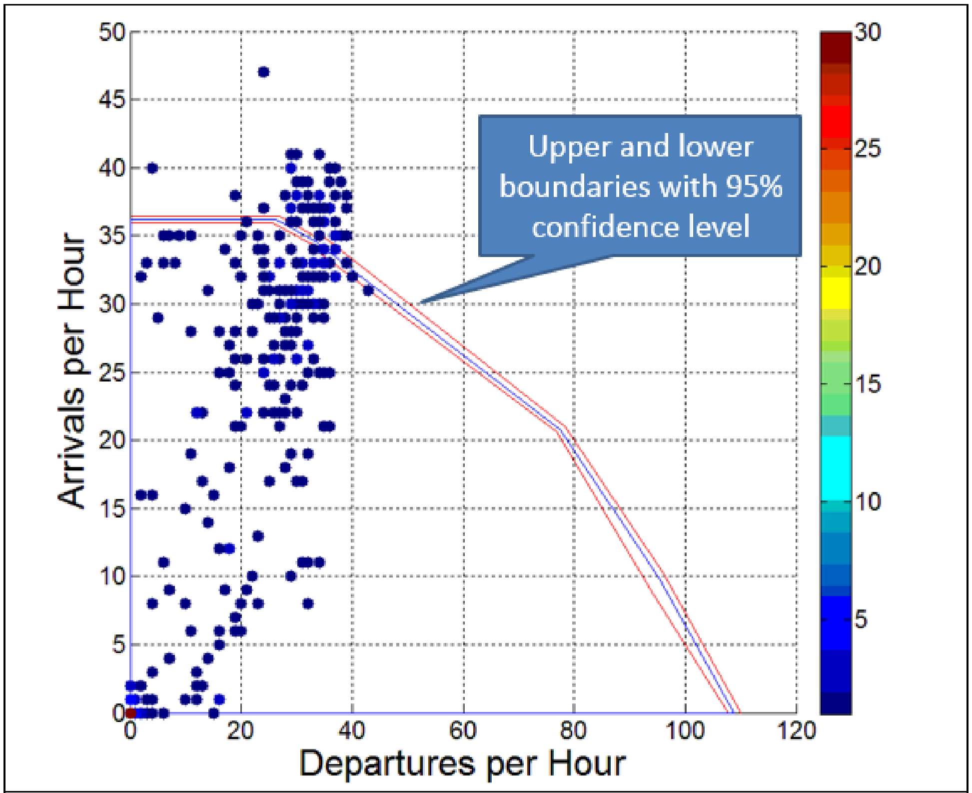
In the same way, we estimated confidence levels and variances for several airports with different runway configuration and the results for all scenarios are reasonable. Pareto boundaries with 95% of confidence levels are all within few aircraft from the mean. Figure 33 shows the Pareto boundaries and confidence levels for selected airports: a single runway airport and for Los Angeles International airport (LAX).

Table 23. Mean and Variance of Estimated Capacity.

Arrivals		Anderson-Darling Normality Test		Bootstrap	Mean 95% Confidence Intervals			St. Dev. 95% Confidence Intervals	
Mean (# of Aircraft)	St. Dev.	Result*	P-score	Mean	Upper	Lower	St. Dev.	Upper	Lower
9.83	1.85	1	0.00	9.85	10.22	8.72	1.75	2.62	1.13
20.80	0.58	0	0.33	20.80	21.04	20.63	0.56	0.76	0.46
34.38	1.04	0	0.43	34.40	34.85	33.99	1.03	1.31	0.84
34.52	0.63	0	0.25	34.52	34.77	34.34	0.61	0.77	0.53
36.24	0.84	0	0.17	36.24	36.48	35.95	0.80	0.97	0.72

Departures		Anderson-Darling Normality Test		Bootstrap	Mean 95% Confidence Intervals			St. Dev. 95% Confidence Intervals	
Mean (# of Aircraft)	St. Dev.	Result*	P-score	Mean	Upper	Lower	St. Dev.	Upper	Lower
108.76	2.86	0	0.24	108.68	110.04	107.77	2.82	3.62	2.10
95.27	2.29	0	0.34	95.30	96.09	94.29	2.25	2.71	1.74
77.49	1.74	0	0.20	77.45	78.27	76.80	1.65	2.49	1.36
34.14	2.40	0	0.33	34.06	35.20	33.32	2.36	2.98	1.99
33.62	1.60	0	0.38	33.63	34.14	32.79	1.55	2.15	1.10
26.32	1.46	0	0.54	26.31	26.89	25.79	1.42	1.82	1.16

* 1= the test rejects the null hypothesis that the data comes from a normal distribution at the 5% significance level



The maximum variance is 3.1 aircraft for arrivals and 8 aircraft for departures

Figure 32. Confidence Levels for Pareto Boundaries.

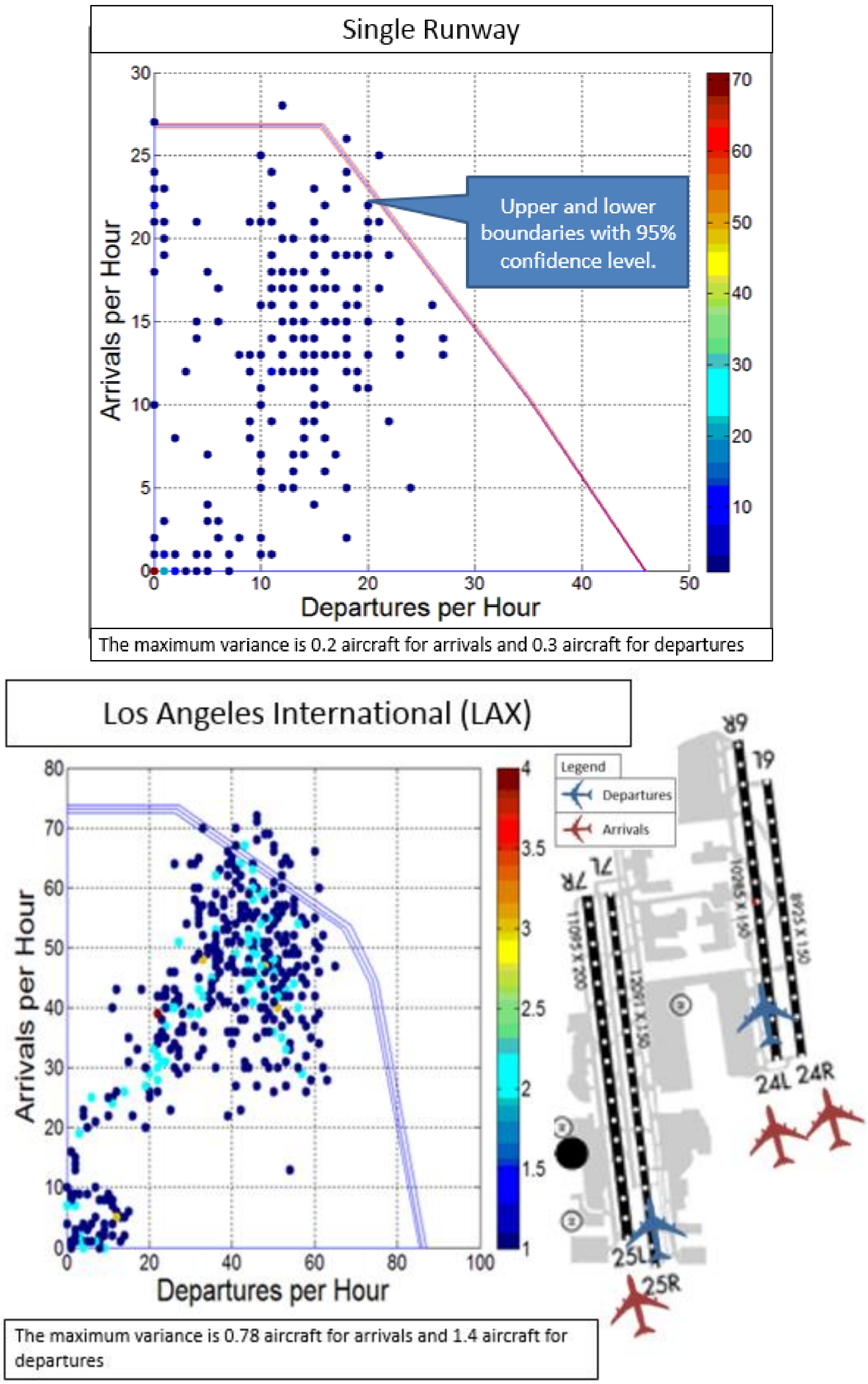


Figure 33. Confidence Levels for Pareto Boundaries at Selected Airports.

3.3. Conclusions and Recommendations

3.3.1. Conclusions

The Airport Runway Capacity model developed in this study calculates the capacity of an airport using a hybrid method that blends algorithms of analytical models and more sophisticated discrete-event simulation software. Airports with complex runway configurations and numerous runways can be analyzed using a numerical superposition method. In the model, random arriving and departing flights are generated to create an ordered sequence of flights by using blocking rules and minimum separation distances. The capacity of an airport is then estimated by taking the inverse of the expected headway between all aircraft created in the simulation.

A graphic user interface has been developed to maximize the usability of the model. The user has maximum flexibility to keep the default values estimated by this study or modify any of the parameters in the model.

The model has been validated against the results presented in the FAA benchmark report. The model results produced are consistent for different models. Another validation performed was comparing the model results with the effective hourly arrivals and departures operations declared by each airport in the FAA ASPM data. This validation has shown consistent results with most of the observations within the Pareto diagram for many of the airports studied. Finally, we validated the change of trends in the runway capacity Pareto diagram when the intersection point of two intersecting runways is shifted towards the runways ends or when the percentage for each type of aircraft that operates at a specific airport is modified. The trends observed were consisted with our predictions.

We can confirm that the model developed by this effort is consistent with runway capacities reported in the literature.

3.3.2. Recommendations

The capacity model developed the capability to estimate capacity for 250 airports in the US contained in the NASA ACES simulation model. This model can be further extended and refined with some features that would make the model even more realistic. For example, it could be possible to extend the number of dependent runways beyond three runways. The model could be extended to study three parallel runways or three intersecting runways. Because of the scope and the length of this study, some default values and parameters were estimated and could therefore use airport operational data to provide more accurate input values for the model. The model is limited to 250 airports, which can be easily extended to include more GA and smaller airports in the NAS. Furthermore, more validation and verification should be performed with different sets of airports and to compare the results with other models.

It is important to note that, just as the number and configuration of runways may not be the only constraint in airport capacity. Other factors are the number of gates and the configuration of taxiways. For instance, an airport can built many runways to maximize capacity but if there are only a dozen gates available, then the maximum number of operations allowable at the airport is limited by the number of gates. Including these values in the model would further advance the model to the real capacity and constrains of each airport.

4. Conclusions

This thesis developed two distinct models to estimated demand and capacity components in the NextGen system. Both models have showed consistent results with the initial scope of work .The calibrated Multinomial Logit Model has shown that all three attributes – Travel Cost, In-vehicle Travel Time and Out-of-Vehicle Time- included in the utility functions are significant to commuters' mode choice decision making. On the other hand, the airport capacity model developed provides an intuitive and effective tool to estimate airport runway capacity of existing and future runway configurations.

Mode Choice Model

The Out-of-Vehicle Travel Time plays a critical role in the commuter decision process since the calibrated coefficient was significantly higher than travel cost and in-vehicle travel time.

The predicted demand for Zip Vehicles is low for both \$0.5 and \$1.0 seat/mile travel cost. This is driven by the high average transfer time to/from airports calculated for each urban area in our study. Since the Zip Vehicle would require a 2,000 feet runway for takeoff and landing operations, most commuters would have to drive, on average, more than 20-25 minutes each way to reach an airport and to their workplace from an airport. The competition with auto and transit in our model makes the Zip Vehicle unattractive to commuters and therefore the ridership is predicted to be low.

Ultimately, this study estimated the potential demand in the New York area and Southern California if the Zip Aircraft is converted to VTOL technology. The results showed that the average transfer time from/to airports dropped by 1/3 in the New York area and by 2/3 for Southern California. This lower transfer time to and from airports leads to a more competitive Zip Vehicle with increased demand for both areas. We believe that the demand for Zip Vehicles would increase if Vertical Take-off (VTOC) technology is adopted. Similarly, the Zip Vehicle technology seems marginally feasible if the airfare and vehicle costs are kept below one dollar/mile.

Airport Capacity Model

The Airport Runway Capacity model developed in this study calculates the capacity of an airport using a hybrid methodology that includes simple analytical model techniques and more sophisticated simulation methods. The model is capable of analyzing existing and future runway operations and airports with complex runway configurations using a numerical superposition method.

A graphic user interface has been developed to improve the usability of the model. The user has flexibility to keep default values estimated in our study or modify any of the various parameters of the model.

The model has been validated using the benchmark report of the FAA for airport capacity, and the results produced are consistent with FAA results. Another validation effort superimposed the results of the model with the effective hourly arrival and departure operations declared by each airport in the ASPM top 77 airport list. This validation method has shown consistent results with most of the observations within the Pareto diagram for many of the airports studied. Finally, we validated the change of trends in the Pareto diagram when the intersection point of two intersecting runways is moved or when the fleet mix of an airport is changed from small to heavy aircraft. All the trends studied were consisted with predictions done using analytical methods.

We conclude that the model developed by this study can be used as a quick solution to estimate airport capacity.

In conclusion, both capacity and demand models were developed to predict the status quo of the demand for Auto and Transit in seven US metropolitan areas and airport capacity for 250 airports in the US. Secondly, these studies looked into the future of the aviation industry by forecasting the demand for a futuristic Zip Vehicle and estimating the capacity of airports under Next Gen operations.

5. Recommendations

Mode Choice Model

The mode choice model calibrated using more sophisticated methods to calculate travel time and travel cost can enhance the baseline model. For instance, the Los Angeles area analysis showed high sensitivity to Travel Cost, due to the lack of well-established mass transit system in Los Angeles and due to the influence of parametric calculation of Transit Travel Cost.

A lack of transit observations limited the analysis of this study. The study was limited to a few values of different income groups. One way to solve this issue is to include more metropolitan areas in the study. In this way, more observations and wider sets of airports and heliports become available.

There is a lack of General Aviation airports near Metropolitan Areas, such as New York City, DC, Dallas, etc. Not only there are no GA airports in the most densely populated areas, but most of the times also close by counties lack of adequate infrastructures for Zip Vehicles. For example, Manhattan in New York City does not have airports with 2,000 paved runways. The Bronx county and the areas in northern Manhattan also lack of airports that could be employed by airports for Zip Vehicles with fixed wing technology. The same reasoning applies to DC, Houston and the Dallas areas.

A mode choice model based on a database such as the NHTS represents a first-order analysis of possible demand for Zip Vehicle technology. Alternatively, stochastic methods that use Monte Carlo simulations can be used to include family income level in the study. Further refinements would involve collecting survey data using hypothetical commuter trips with inclusion of zip vehicle cost and travel time estimates. Commuters can be questioned directly on whether they would be willing to take this new commuting aircraft and under what conditions, with the aim of including ZIP aircraft perceived reliability and desirability.

Airport Capacity Model

The capacity model developed has proven to be consistent with estimates of the hourly throughput capacity for 250 airports in the US. This model can be further extended and refined with multiple features that would make the model even more accurate and precise. For example, it could be possible to extend the number of runways estimated for each given set of dependent runways, for example 3 parallel runways or 3 intersecting runways. Because of the scope and the length of this study, some default values and parameters were simply estimated and could therefore use more field data to enhance the model.

A user can choose a limited airport set with currently 250 airports, this list could easily be extended to include more GA and smaller airports in the NAS. Furthermore, more validation and verification should be performed with different sets of airports and comparing with results obtained in other models.

It is important to note that, just the number and configuration of runways may not be the only constraints in airport capacity modeling. Other factors are the number of gates and the configuration of taxiways. For instance, an airport can built numerous runways to maximize capacity but if there are only a dozen gates available, then the maximum number of operations allowable at the airport is limited by the number of gates. Including these values in the model would further advance the model to the real capacity and constrains of each airport.

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Appendix

Appendix A – List of Functions in Matlab for the Capacity Model

Function Name	Description	Sub function of
Main_OneAirport_Capacity	Main function for the model.	None
InputDataFile	All the different input parameters for the model are recalled using this function	None
ImportData_GUI	Transfers input text files from user interface into Matlab	Main_OneAirport_Capacity
Separation_Matrices	This function uses the runway information to estimate the interaction and separation matrices between runways.	Main_OneAirport_Capacity
Separation_I_Calc	Calculate separation distances between intersecting runways	Separation_Matrices
Separation_P_Calc	Calculate separation distances between centerlines of parallel runways	Separation_Matrices
Separation_ST_Calc	Calculate stagger distance between parallel runways	Separation_Matrices
Runway_Conf_ArrDept	Transforms the runways used for arrivals and departures into a more handy vector	Main_OneAirport_Capacity
RemoveNotUsedRunways	Remove runways that are not used in the scenario	Main_OneAirport_Capacity
FindDependentRunways	Find sets of independent runways	Main_OneAirport_Capacity
Crossing_TwoRwy_Dependency	Check whether two crossing path runways are dependent from each other	FindDependentRunways
Parallel_Dependency	Check whether two or more parallel runways are dependent from each other	FindDependentRunways
Parallel_TwoRwy_Dependency	Check whether sets of two parallel runways are dependent from each other	Parallel_Dependency
Find_Primary_Secondary_Intersect_Parallel	Decides which runway ends are the primary and secondary arrival/departure streams	Main_OneAirport_Capacity
WhatRunwayConfiguration	This function checks how many dependent runways the scenario is calculating and recalls the right sub-function	Main_OneAirport_Capacity

SingleRunway	This function estimates the capacity for a single runways used in mix mode (arrivals and departures)	WhatRunwayConfiguration
SingleRunway_1ops_Arr	This function estimates the capacity for a single runways used for arrivals	WhatRunwayConfiguration
SingleRunway_1ops_Dept	This function estimates the capacity for a single runways used for departures	WhatRunwayConfiguration
TwoParallelRunways	Main function to estimate the capacity for two parallel runways	WhatRunwayConfiguration
TwoIntersectingRunways_Main	Main function to estimate the capacity for two intersecting runways	WhatRunwayConfiguration
TwoParallel_OneIntersecting_Main	Main function to estimate the capacity for three or more runways	WhatRunwayConfiguration
Runway_Operation_Matrix	Calculate a matrix for runway arrivals and departures, the same as a separation matrix.	WhatRunwayConfiguration
Four_Runway_Possible	Establish whether the four runways case is feasible in the model	WhatRunwayConfiguration
RandNumGen_GroupAssignment_Dept	Assign aircraft group attribute information to a set of random aircrafts (arrivals)	Multiple
RandNumGen_GroupAssignment_Arr	Assign aircraft group attribute information to a set of random aircrafts (departures)	Multiple
Parallel_Dependent	Check whether the distance between parallel runways is large enough to run independent operations.	TwoParallelRunways
FleetMix_FinalAdj	Adjusts the operations assigned to a short runway	Multiple
Parallel_Arrival_Below2500_Jun02_FleetMix	This function estimates the arrival operations for two parallel runways that are dependent from each other and follow the 1.5nm diagonal rule	TwoParallelRunways
Parallel_DepArrival_Above2400_Jun03_FleetMix	This function estimates the arrival operations for two parallel runways that are dependent from each other and follow the 1nm diagonal rule	TwoParallelRunways
Parallel_TwoIndepDept_Jun04_FleetMix	This function estimates the departure operations for two parallel runways that are dependent from each other	TwoParallelRunways

Parallel_OneIndepDept_Mar15	This function estimates the departure operations for two parallel runways but departures only on one runways	TwoParallelRunways
Parallel_TwoDependentDept_Mar15	This function estimates the departure operations for two parallel runways that are independent from each other	TwoParallelRunways
Pareto_Diagram_OneArrival_Intersect	Estimates the capacity for two intersecting runways with arrivals only on one of the two runways	TwoIntersectingRunways_Main
Pareto_Diagram_TwoArrivals_Intersect	Estimates the capacity for two intersecting runways with arrivals on both runways	TwoIntersectingRunways_Main
Main_Arrival_InterDepartures	This function estimates the arrival operations for two intersecting runways with arrivals on one runway	Pareto_Diagram_OneArrival_Intersect
IntersectRwy_FullOps_Main	This function estimates the arrival operations for two intersecting runways with arrivals on both runways	Pareto_Diagram_TwoArrivals_Intersect
IntersectDept_1Rwy_Mar10	This function estimates the departures operations for two intersecting runways with departures on one runway - one arrival stream	Main_Arrival_InterDepartures - IntersectRwy_FullOps_Main
IntersectDept_May27	This function estimates the departures operations for two intersecting runways with departures on both runways (intersect first after arrivals) - one arrival stream	Main_Arrival_InterDepartures - IntersectRwy_FullOps_Main
SameRwyDept_May27	This function estimates the departures operations for two intersecting runways with departures on both runways (same runway first after arrivals) - one arrival stream	Main_Arrival_InterDepartures - IntersectRwy_FullOps_Main
IntersectDept_BS_Mar27	This function estimates the departures operations for secondary departures (same runway first after arrivals)	Multiple
SameRwyDept_BS_Mar27	This function estimates the departures operations for secondary departures (intersect first after arrivals)	Multiple

IntersectDept_1Rwy_IntersFull_Mar4	This function estimates the departures operations for two intersecting runways with departures on one runway - two arrival stream	IntersectRwy_FullOps_Main
IntersectDept_IntersFull_Mar27	This function estimates the departures operations for two intersecting runways with departures on both runways (intersect first after arrivals) - two arrival stream	IntersectRwy_FullOps_Main
SameRwyDept_IntersFull_Mar27	This function estimates the departures operations for two intersecting runways with departures on both runways (same runway first after arrivals) - two arrival stream	IntersectRwy_FullOps_Main
ParetoDiagram_3Rwy_2ParallArrivalsAndDept	Main function to estimate the capacity for three runways	TwoIntersectingRunways_Main
ParetoDiagram_4Rwy_2ParallArrivalsAndDept	Main function to estimate the capacity for four parallel runways	TwoIntersectingRunways_Main
IntersectRwy_ArrivalsforParallel_Apr1	This function calculates the times at intersection for operations on parallel runways that have an intersecting runway.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept
Parallel_Intersect_Arrivals_Jun09_FleetMix	Estimates arrivals on the intersecting runway in the case of 3 runways.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept
FleetMix_Recab	This function redistribute fleet mix to the different runways at the airport.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept
Parallel_3rwy_TwoDependentDept_FleetMix	This function estimates the departure operations for two parallel runways that are dependent from each other. Three runway case.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept

TotalOperations_3rwy	This function combines together arrivals and departures operations into one single variable. Three runways case	ParetoDiagram_3Rwy_2ParallArrivalsAndDept
TotalOperations_4rwy	This function combines together arrivals and departures operations into one single variable. Four runways case	ParetoDiagram_4Rwy_2ParallArrivalsAndDept
IntersectDept_3rwy_2parallel_full_Mar25	Estimates departure operations for the intersecting runway in the three runway case.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept
Parallel_3rwy_TwoIndepDept	This function estimates the departure operations for two parallel runways that are independent from each other. Three runway case.	ParetoDiagram_3Rwy_2ParallArrivalsAndDept - ParetoDiagram_4Rwy_2ParallArrivalsAndDept
Intersect_SecondaryArrival_FleetMix	Estimates arrivals on the secondary intersecting runway in the case of 3 runways. Only two arrival streams on one of the two parallel runways	Parallel_Intersect_Arrivals_Jun09_FleetMix
Parallel_DepArrivalsBelow2500_Secondary_FleetMix	Three runways. This function estimates arrivals on the two parallel runways when the two runways are dependent from each other	Parallel_Intersect_Arrivals_Jun09_FleetMix
Parallel_Above2400Arr_Secondary_FleetMix	Three runways. This function estimates arrivals on the two parallel runways when the two runways are independent from each other	Parallel_Intersect_Arrivals_Jun09_FleetMix
SameRwyDept_BS_parallel_Mar29	This function estimates the departures operations for secondary departures. Three-runway case.	Parallel_3rwy_TwoIndepDept - Parallel_3rwy_TwoDependentDept_FleetMix
RwyArrDept_FinalCheck	This function checks whether a scenario with two or more runways has no arrival or departure streams.	Main_OneAirport_Capacity
Paretodiagrams_combine	Combine two Pareto diagrams with a numerical superposition method	Main_OneAirport_Capacity

plotRNWCONF_ADR_AAR_2	Plots the ASPM effective arrival and departure rate on the Pareto diagram	Main_OneAirport_Capacity
Trajectory_InputVariable	When the aircraft information is not defined in the GUI, this function calculates the trajectory matrix for arrival and departure aircraft.	ImportData_GUI
PersonalizedGrouping	For the personalized grouping option, this function defines a group number for each aircraft in the BADA list.	Trajectory_InputVariable
Weight_Calc	Calculates the weight for each aircraft in its own group using FAA aircraft registration registry and annual usage	Trajectory_InputVariable
Trajectory_ApproachSpeedAndMRL	Estimate for each aircraft group the approach speed, minimum runway length and ROT	Trajectory_InputVariable
DepartureProfiles_Calc	Assign a departure profile to each aircraft group	Trajectory_InputVariable
ACM_ShowParetoDiagram	This m-file shows the desired pareto diagram in VB	Main_OneAirport_Capacity