Proceedings of the 2005 Winter Simulation Conference
M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, eds.

SIMULATING AIR TAXI NETWORKS

Philippe A. Bonnefoy

Massachusetts Institute of Technology
77 Massachusetts Avenue
Cambridge, MA 02139, U.S.A.

ABSTRACT

The U.S. air transportation industry is about to experience the emergence of on-demand air taxi networks enabled by a new generation of Very Light Jets (VLJs). These new networks are unique in many ways and the top down design approach of air taxi enterprises generates challenging and complex questions. Simulation was found to be an essential technique for understanding, analyzing and evaluating the complex behavior of air taxi networks.

The Air Taxi Network Simulator is a fast-time simulator that replicates the operations of fleets of air taxi aircraft over a network of hundreds of airports. Its capabilities include demand modeling, trip generation, aircraft routing and pilot assignment, unscheduled maintenance events with recovery mechanisms, etc. It provides key performance metrics that enable decision makers to test and evaluate various strategic and tactical scenarios.

1 INTRODUCTION

1.1 Structural Changes in the Air Transportation Industry

The air transportation industry has experienced significant structural changes over the last decades. From a policy perspective, the most significant shift occurred in 1978 when the airline industry was deregulated. Prices and market restrictions that were previously imposed on airlines were lifted. Legacy airlines focused on the development and refinement of the hub-and-spoke system based on the concept of demand consolidation. With this type of operations, airlines inherited a specific cost structure (due to peaked schedules and low aircraft utilization) and a lack of flexibility and robustness. In the 1980s, low-cost carriers emerged. These enterprises were driven by a new process paradigm with simpler and more efficient point-to-point operations. Low-cost carriers, especially Southwest airlines, have focused their business model on the utilization of fleets with a single aircraft type. From an infrastructure stand point, they used underutilized regional airports that ultimately led to the emergence of secondary airports (Bonnefoy 2004). This phenomenon resulted in the use of a wider set of airports, making the system less dependent on a few key major airports. It also meant better access to air transportation for local communities, lower overall traveling time and better robustness of the system since a region was no longer dependent on one single airport.

After deregulation, which gave airlines increased pricing power, carriers extensively used yield management, later called revenue management, in order to maximize the generation of revenues.

In the 1990s, the air transportation industry was driven by an information technology shift. Real time information sharing of seat availability and fares through either search engines or airline specific websites allowed better transparency of products availability. Combined with the growing market share of low-cost carriers, yield decreased continuously. In the meantime, a new generation of 50 to 90 seat aircraft called regional jets was used extensively by airlines to offer higher flight frequencies on markets with thin demand.

In the unscheduled air transportation domain, the major breakthrough occurred in the mid 1980s with the emergence of the fractional ownership program operators, such as NetJets (1986), Flexjet (1995) and Flight Options (1998). This concept allowed corporations or individuals to share an aircraft for a fraction of the total cost.

Looking ahead, many more changes are likely to occur in the air transportation industry. One of them being the potential entry of Very Light Jets (VLJs), resulting in the emergence of new operating and business models.

1.2 Emergence of Air Taxi Networks

A new generation of four to six seat jet aircraft, called Very Light Jets (VLJs), is about to enter the market for a fraction (roughly one third to half) of the price of current similar jets and significantly lower operating costs. As of 2005, the major players in this market were Eclipse Aviation (with the

Eclipse500), Cessna (Mustang), Adam Aircraft (A700) and Embraer (EMB-VLJ). Several other international and U.S. aircraft manufacturers have entered or are about to enter the race towards certification and first deliveries.

These new Very Light Jets, and the current set of uncongested airports, will allow the emergence of new national on-demand, regional based air-taxi networks. The operators of such networks will own, operate, crew and maintain the aircraft in-house. With significantly lower costs than the current unscheduled air service operators and large numbers of single category aircraft, these new air taxi operators promise to provide low fare on-demand personal transportation.

An analogy can be drawn between the low-cost carriers and air taxi networks, respectively from the scheduled and unscheduled air transportation industry. Like legacy carriers, existing corporate/business aviation operators (e.g. fractional ownership program operators, charters, etc.) carry some inherited characteristics such as multi-aircraft type fleets, low aircraft utilization, high cost structure. Air taxi operators may be viewed as the low-cost carriers of the business aviation industry with single type of aircraft, higher aircraft utilization, and low-cost structure.

From a demand stand point, the attractiveness of these services resides in the lower average door-to-door travel time, its reliability and its better affordability than current comparable services. The lower time of travel is achieved though the use of a wider set of airports (than the current set of airports utilized by scheduled airlines), allowing point-to-point flights between uncongested airports closer to the customers' doors. This travel time attribute will become even more significant for customers when the capacity crisis at major airports will generate delays exceeding those experienced in 2000. By the end of 2005, volume of operations generated by air carriers and commuters are expected to reach and exceed the year 2000 levels. They are forecasted to grow at an annual rate of 2.3% and 3.2% respectively beyond 2005 (FAA 2005a). With limited capacity improvement, based on current indications, capacity crises are likely to occur in the summer of 2006 or 2007, which corresponds to the time when the on-demand services will become available at small uncongested regional airports.

The better affordability of air taxi services is achieved through lower aircraft acquisition and operating costs, lower airport landing fees but also from operational efficiencies due to economies of density.

However, there are challenges related to the creation and the operation of air taxi networks. Since the concept is based on on-demand service, it is unlikely that the arrival airport of a revenue flight corresponds to the departure airport of the next revenue flight. Therefore, non revenue flights, also called repositioning flights, must exist in order to connect the destination airport of one revenue flight to the departure airport of the next revenue flight operated by the same aircraft. Because repositioning flights are only generating costs and no revenue (unless they are offered as semi-scheduled flights at discounted price), there are strong incentives to minimize them both in counts and stage length. This is achieved at the operational level by constructing coherent schedules, but it also depends on the strategic and tactical decisions that are taken earlier during the network and enterprise design process. There are great challenges and questions posed by the design of air taxi enterprises, such as:

- influence of size and density of the fleet over a given network,
- impact of network configuration on the fleet utilization,
- influence of levels and concentration of demand on fleet performance,
- influence of maintenance base capacity on the utilization of the fleet,
- impact of the location and the number of maintenance and pilot bases on the efficiency of the operations, etc.

1.3 Motivation for Developing a Simulation Tool

Air taxi networks are complex systems that involve hundreds of aircraft and many times more pilots. These assets and human capital move quickly over an un-structured network composed of large sets of airports.

Modeling such a system involves both macro (strategic) and micro (operational) levels of abstraction. In addition, the behavior of fleets of air taxi networks involves hundreds of input variables. The components of the system are tightly coupled and the performance metrics are nonlinear. The operations are also constrained by federal regulations and company specific policies (pilot flight and duty time, time between maintenance checks, etc.). As a result, it is difficult to be confident in the results of an aggregate model. Therefore, there was the need to build a simulation model in order to capture and understand the complex dynamics of air taxi networks, and test the impact of various strategic and tactical decisions on the performance of the system.

Even though there are multiple simulators for scheduled airline operations such as MEANS (Clarke 2004), SimAir (Lee 2003). These models could not be used due to the unique nature of the air taxi operations. In addition, no tool had been previously developed to address this specific problem. A simulation tool was then designed, built, tested and implemented.

This paper provides a description of the architecture and the testing capabilities of this simulator. Finally, it presents a sample of results from sensitivity analyses and scenario testing that are relevant to the air-taxi enterprise architecture process.

2 OVERVIEW OF THE AIR TAXI NETWORK SIMULATOR

The Air Taxi Network Simulator (ATNS) is a fast-time simulator that was designed to address strategic and tactical level challenges by replicating the behavior of a fleet of air taxi aircraft (typically 25 to 100 aircraft) over diverse networks of airports. The most commonly tested networks did include airports located within 500 miles of a core metropolitan area. For dense networks, such as the northeastern part the United States, the size of the network corresponds roughly to 780 airports. With potentially a dozen similar networks in the U.S., this implies that with 100 aircraft per network the overall fleet could reach over one thousand aircraft. ATNS was usually tested to replicate the behavior of the fleet over one complete year of operation.

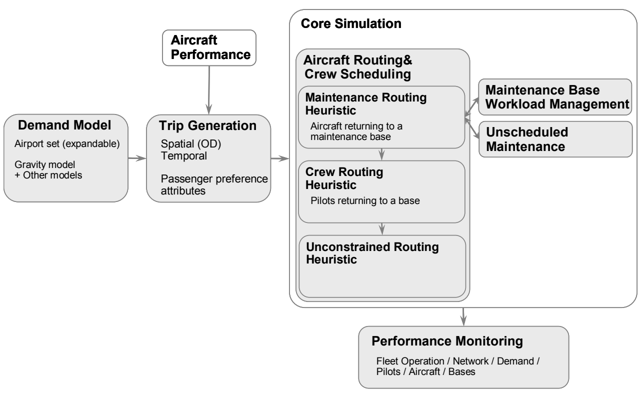

Figure 1 : High Level Architecture of ATNS

ATNS was designed using a modular architecture (Figure 1). It includes a demand module which feeds a trip generation module that generates individual flight requests. These flight requests are then utilized in the day-to-day execution of the flights. The core part of the simulation assigns flights to aircraft and pilots and executes these sequences of flights. Other additional modules such as maintenance facility management, unscheduled maintenance event generation and performance monitoring will be described in greater details in the next sections. This modular approach with well defined interfaces and data flows allowed the development of the simulator to follow evolving specifications as well as refinements of each module independently of the others.

3 ARCHITECTURE AND CAPABILITIES OF THE AIR TAXI NETWORK SIMULATOR

3.1 Demand Models

In the case of scheduled services, the fulfillment of travel requests (individual demand) is driven by the supply defined in terms of the number of seats (capacity) on given routes (airline network), with frequencies and departure/arrival times usually defined several months in advance. In contrast, air taxi operations are driven by individual demand. A passenger making a reservation, by phone or online, will choose the origin, the destination and the earliest time of departure and the latest time of arrival based purely on his preferences, without being constrained by published schedules. The passenger also has the opportunity to express his willingness to share an aircraft, therefore allowing consolidation of demand whenever possible.

The spatial component of a flight request (origin/ destination) is only constrained by the set of airports that the air taxi operator agrees to serve. Whether an airport can be utilized or not, is usually defined by aircraft performance characteristics such as the take-off balanced field length. This requirement must be lower than the minimum runway length at the airport. Runway requirements for Very Light Jets are likely to be approximately 3000 ft. The simulator includes an airport database of 3200 public airports (of which 730 are equipped with at least one ILS) located in the continental United States. All of these airports are potentially useable by Very Light Jets. Depending on the goal and the analysis to be performed any subset of airports can be selected. The temporal component of a flight request is generally unconstrained.

In the simulation, the generation of flight requests is based on demand models that capture both the spatial and temporal components. The spatial distribution of flights, Origin and Destination (ODs), is captured by a gravity model including both the distribution of population and airport specific constraints such as access, capacity restrictions, operational limitations, etc. A gravity model approach was used to distribute population to airports, using U.S. Census 2000 population distribution of 65,433 census tracts (USCB 2000). In order to take into account potential VLJ airport access restrictions, some airports such as the slot restricted major airports (La Guardia, Chicago O'Hare, Washington National and New York J.F. Kennedy) were excluded from the set of airports. An airport specific weighting factor (ranging from 0% to 100%) was also used to capture constraints such as access to a specific airport, operational limitations, etc. This factor was primarily based on industry experience. The weight assigned to a specific airport was defined as follows:

$$P'_i = WF_i \sum_{j \in At} Pop_j \qquad (1)$$

where Pop_j is the population of Census tract j. WF_i is the airport weighting factor capturing the access constraints around airport i and A_t is the set of Census tracts that have the shortest distance to airport i.

Based on the gravity model, the probability of a flight being generated on an arc from airport i to airport j in the network was defined by:

$$P_{i,j} = \frac{P'_i . P'_j}{(\sum_{i \in A} P'_i)^2} . \qquad (2)$$

For a network such as the North East network (airports within 500 miles of the New York metropolitan area) this corresponds to approximately 600,000 OD pairs.

This initial gravity model was kept simple. Using the advantages of the modular architecture of the simulator this module had the ability to be refined based on more accurate demand models including income distributions and alternative modes of transportation such as commercial air services (OD market from BTS DB1 data), automobiles, etc. In addition, as the concept of air taxi networks becomes more mature, detailed marketing studies and surveys can be used to refine and calibrate the demand model.

In order to assess the spatial sensitivity of demand distribution, an alternate demand model was designed. It was based on the notion of concentration of traffic on the selected set of airports. Using the ordered vector of airports from the gravity model, the airport weights P'_i were recomputed using a Pareto distribution. Two user-defined distribution control points (e.g. 20% of the airports handle 80% of the traffic and 50% of the airports handle 99% of the traffic) were used to define this function. With the new airport weights, new OD probabilities were recomputed. Section 4.1.2 gives an illustration of the use of this option.

The temporal distribution of flights departure times was based on various factors. First, each flight departure and arrival times were composed of an earliest and a latest time that were set by the customer. In order to generate the typical two peak daily demand curve of departures and arrivals, several parameters and distributions were entered as input. The distribution of earliest time of departure of the first leg, the distribution of time difference between latest and earliest time of departures, and the percentage of flight that have a return leg. In addition to the daily distribution of demand, an annual distribution of demand captures seasonality effects. The annual volume of flight requests is set at the beginning of each simulation as an input variable. This allows running sensitivity analyses of demand levels and their impacts on fleet performance.

Both the spatial and the temporal distributions feed the trip generation module that generates individual flight requests.

3.2 Trip Generation

Monte Carlo Simulation theory and techniques were utilized to generate individual flight requests. Flight requests were composed of several attributes:

- Origin / Destination,
- Earliest / Latest Time of Departure,
- Earliest / Latest Time of Arrival,
- Return leg,
- Number of passengers,
- Willingness of passengers to share a flight with other customers.

Several steps were required before generating flight requests. First the annual demand volume (total number of flights over one year) was split by months using the annual distribution of traffic. Monthly demand volume was used to generate the daily volume of flight requests.

At the end of each day, flight requests were generated and were submitted for rejection or acceptance in which case they were entered in the schedule.

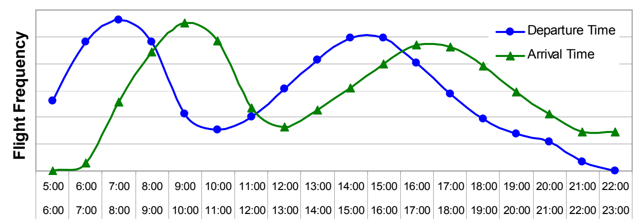

Figure 2: Example of Daily Departure and Arrival Time Distribution

3.3 Aircraft Performance Module

Because Very Light Jets were in preliminary development and not certified at the time of the study, an aircraft performance input module was built allowing the testing of different aircraft types with various performance characteristics. Flight time functions, maximum range, fuel consumption, and aircraft reliability functions are among the set of parameters that can be entered.

3.4 Aircraft Routing & Crew Scheduling

Introducing demand selection and scheduling capabilities in a Monte Carlo simulation was a challenge. Multi-million dollar and time consuming software are used by scheduled and low-cost airlines to build flight schedules. The use of the characteristics of the problem constraints enabled the creation of aircraft and pilot daily schedules.

From the mapping of the operational processes of air-taxi enterprises (Bonnefoy 2002), it was found that fleet management was based on several fundamental constraints:

- ***Maintenance Constraints:*** After a certain number of hours of flight (or number of cycles) an aircraft is required, by regulations, to return to a maintenance base and go through various maintenance checks. Typically the checks occur every 1200, 300 and 50 hours. This implies that an aircraft must return to a specific airport (or set of airports) when it operates within a few hours of the next maintenance check. Aircraft routings can then be viewed as cycles or sequences of revenues and non revenues flights in and out of a specific maintenance base.

- ***Pilot Constraints:*** A pilot is generally assigned to a specific base and must return to its base at least every 3 or 4 days. In addition to these company specific requirements, pilots must comply with Federal Aviation Regulations Part 135 and Part 91 (FAA 2005b) flight and duty time regulations that specify the daily maximum amount of flight and duty time and the minimum amount of rest. For example, under Part 135 operations (regulations governing revenue flights) pilots are not allowed to fly more than 10 hours, work (duty time) more than 14 hours every day, and need a minimum rest of 10 hours between two consecutive days of work.

These routing constraints do not have the same weight. For routing purposes, the maintenance requirements are hard constraints. They are dictated by federal regulations and an aircraft cannot go beyond the authorized number of hours between checks otherwise it is illegal to fly and is therefore grounded. The pilots' constraints (3-4 day cycles) are somewhat softer constraints since they are based on company's internal human resource management policies (as long as assignments do not violate FAA flight and duty time regulations). Recognizing the characteristics of these constraints sequential aircraft routing and pilot assignment heuristics were designed:

- ***Maintenance Routing Heuristic:*** This heuristic generates aircraft routings that bring aircraft back to their maintenance base at the end of the day when a 1200h, 300h or 50h maintenance check is required. Because the maintenance base is also a pilot base, the pilot constraints are satisfied.
- ***Pilot Routing Heuristic:*** This heuristic generates aircraft routings that bring pilots back to their base at the end of their 4 days of duty. At this point there is no maintenance constraint to be taken into account since these were resolved with the previous heuristic.
- ***Unconstrained (destination) Routing Heuristic:*** The last heuristic creates routings for aircraft that are neither constrained by aircraft maintenance nor pilots. Since aircraft are (in most cases) the most constraining resource, they are the main drivers in the assignment process. Then pilots are paired to an aircraft. The pilot assignment process is based on workload criteria that allow a uniform utilization of human resources.

Aircraft routings and pilot assignments are selected based on an objective function that include revenue, costs (through the non revenue to revenue mileage ratio), idle time and location of the aircraft at the end of the day with adjusting factors for each parameter that could be adjusted to meet management decisions.

3.5 Maintenance Bases Workload Management

The first heuristic of the aircraft routing and crew scheduling module is driven by aircraft maintenance requirements. It generates routings of aircraft that terminate at a maintenance base at the end of the day. The occurrence of maintenance checks is based on aircraft utilization. However, the utilization rates of aircraft are not identical for every aircraft in the fleet. This implies that maintenance checks do not occur in a uniform way. The number of aircraft that need to return to a maintenance base is therefore stochastic. However, the short term capacity of the maintenance base is fixed because of infrastructure (e.g. hangar space) and personnel (e.g. mechanics) constraints. Therefore there is a need to smooth the workload at the maintenance base.

The simulator includes a module that manages the workload of the maintenance base. This module works prior and during the maintenance checks. Before the check, it forecasts the immobilization of the aircraft and plans the daily utilization of aircraft depending on the forecasted workload at the maintenance station. Once the aircraft is in maintenance, the duration of the check can be compressed by rescheduling the maintenance shifts if the maintenance facility is running below its maximum capacity. This strategy has the advantage of releasing aircraft sooner and potentially satisfying unscheduled last minute demand. These early released aircraft can also serve as back up aircraft in case an active aircraft fails.

3.6 Unscheduled Maintenance and Recovery

Because aircraft are not 100% reliable, unscheduled events occur while the aircraft are performing the day to day sequences of flights. Aircraft manufacturer usually capture the probability density function of failures with a Weibull distribution where the failure of an aircraft is a function of time since the last maintenance check.

At the end of each flight, a state of the aircraft (active/failed) is generated by Monte Carlo simulation techniques sampling from the Weibull distribution. If an aircraft is identified as failed, a repair time is generated using a predefined Log Normal distribution. This repair time defines the date and time the aircraft will be released and will become available for dispatch. Concurrently, a flight recovery module takes care of the flights that should have been performed by the failed aircraft. Aircraft that have not been scheduled with flights or have been released from the maintenance base are utilized for these purposes. This module reroutes an aircraft to the departure airport of the first feasible flight and recovers the subsequent flights.

3.7 Performance Monitoring

Because of the nature of on-demand air taxi networks, some of the performance metrics are slightly different than the metrics commonly used in the airline industry. The metrics used for the evaluation of the performance of the fleet are presented in Table 1.

Table 1: Sample of Performance Metrics Generated by the Simulator

Metric Category	*Metrics*
Fleet Operation	• Fleet utilization: fraction of aircraft that are flying in any given day over the entire number of aircraft in the fleet. • Flights per day per aircraft • Revenue mileage per day per aircraft • Non revenue (repositioning) mileage per day per aircraft • Ratio of non revenue vs. revenue flight distances: number of miles of repositioning (non revenue) flight for one mile of revenue flight
Network	• Distribution of traffic (over the set of airports) • Stage length distribution
Demand	• Percentage of flight requests assigned • Temporal and spatial distribution of rejected flight requests
Pilots	• Pilots on duty (Pilot schedules) • Flight time • Duty time • Idle time
Aircraft	• Aircraft remaining time before the next maintenance check (1200h/300h/50h) • Cumulative flight time • Aircraft cycles • Unscheduled events
Bases	• Maintenance facility workload • Pilot availabilities at selected bases

Each of these metrics was generated as simulation output and recorded for analysis purposes. Section 4 provides examples of the type of analyses that were performed.

3.8 Testing

The modular structure of the simulation allowed continuous validation throughout the development of the simulation tool. Each component of the simulator was tested separately. Then the whole simulator was tested under specific conditions using aircraft tracking, pilot tracking, cross comparisons of various performance metrics. Figure 3 shows the example of the routing of an aircraft for one day. Pilot and aircraft tracking and aggregate performance metrics were used to verify that constraints dictated by the federal regulations and company policies such as aircraft maintenance and pilots' flight and duty time, etc. were complied with.

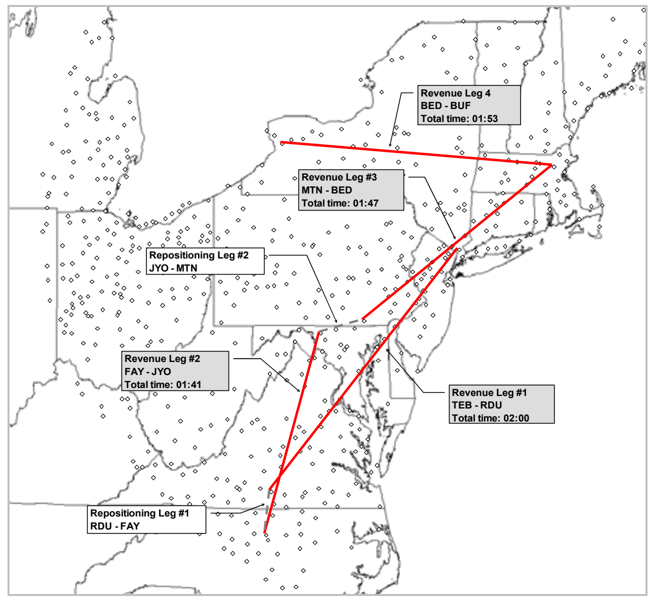

Figure 3 : Example of a daily aircraft routing

4 RESULTS & ANALYSIS

The advantage of fast-time simulation is that it provides an understanding of the behavior of complex systems and allows hypothesis testing without the investments related to real life trial and error testing. Since air taxi companies did not exist at the time of the project, scenario testing was performed in order to assess the impact of various hypotheses that arose from the top down enterprise design. This was done after sensitivity analyses that enabled to gain some understanding of the behavior of the system.

4.1 Simulation Based Sensitivity Analyses

The components of the air taxi network system are tightly coupled. One example of this characteristic was clearly demonstrated with the aircraft routing and crew scheduling module where on some occasions the aircraft constraints were dictating the pilot assignments and vice versa.

The system also exhibits non linear performance due to coupling and boundary conditions, such as fleet size, pilot flight and duty time constraints, network configuration.

The sensitivity analyses enable the assessment of the influence of design variables such as volumes and distribution of demand, fleet size (supply) and network size on the system performance and the definition of acceptable operating envelopes of the system. These analyses were based on the results of several hundred hours of simulation. A sample of the results that were gathered and aggregated is presented as illustrations in the following sections.

4.1.1 Influence of Demand and Supply

Since the air taxi concept is driven by demand, it can be expected that the performance of the fleet will depend on the overall (annual) level of demand. The volume of demand, number of flight requests received, is variable and depends on factors over which the air taxi company has control (price, marketing, advertising aggressiveness, etc.) but also on external factors such as public perception of safety and security, competition, regulations, willingness to travel, etc. Demand volumes forecasting is out of the scope of the simulation tool development and is usually performed through surveys, marketing analyses, etc. Even though demand is taken as an input variable in the simulation and its impacts on the performance of the fleet are significant and must be studied. The other related variable is fleet size (supply). In order to assess the influence of demand volume and fleet size mix on the system performance, a sensitivity analysis was performed on those two variables. Figure 4 illustrates the example of this demand/supply sensitivity analysis on the number of revenue mileage by aircraft by day.

For a given fleet size, an increase in demand volume leads to an increase in performance (measured here in number of revenue miles per day per aircraft). However, since supply is fixed, an increase in demand volume also means that a larger fraction of this demand (flight requests) is not fulfilled. From a customer satisfaction perspective, high levels of demand rejection implies that customers are likely not to make anymore flight request after several unsuccessful trials. Therefore this performance metric must be kept within certain limits which constrain the allowable mix of demand/supply. This approach enables the definition of an acceptable operating envelope. In this case, it means either sizing the fleet properly for a given demand volume or taking actions to stimulate or restrain demand if the fleet size is constrained (through pricing mechanisms, advertising, etc.). Nonlinear behaviors also arise. For example, the number of revenue miles per day levels off under combinations of high demand and low fleet size. This behavior is observed because of the pilot flight and duty time constraints that limit the number of hours –and therefore flights- that an aircraft can perform each day.

Figure 5 also shows an example of fleet utilization for various combinations of demand volume and fleet size. As demand increases and fleet size decreases, the fleet becomes utilized at its maximum. It should also be noticed that this maximum is not 100% since a fraction of the fleet is in maintenance.

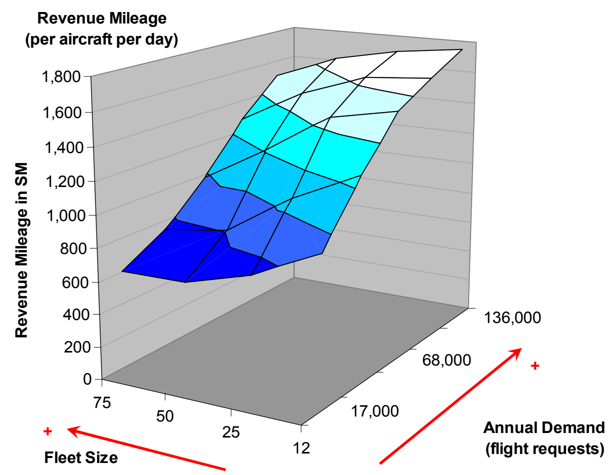

Figure 4 : Influence of Demand and Supply Mix on Revenue Mileage

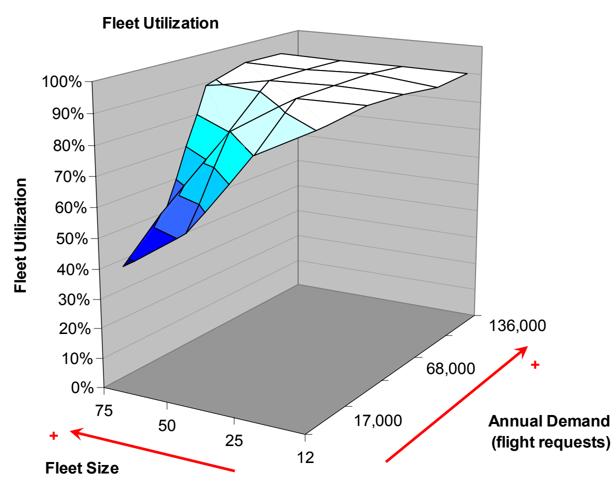

Figure 5 : Influence of Demand and Supply Mix on Fleet Utilization

4.1.2 Influence of Demand Concentration

The air taxi concept is based on the utilization of a large set of small airports (3200 public airports capable of hosting VLJs in the Domestic U.S.). Based on attributes such as population and income distributions some airports (in densely populated metropolitan area) will be more attractive and generate large volume of demand while some airports located in remote areas will have lower annual demand volumes. Therefore the demand is unequally distributed over the set of airports. The distribution of demand impacts the performance of the fleet mainly through the amount and the length of repositioning flights. Because this performance metrics has great impacts on profitability, understanding the impact of demand distribution was fundamental. In order to achieve this goal a sensitivity analysis of demand distribution was performed. The gravity demand model was used as a reference for this study. Demand distributions with various concentrations over the same set of airports were generated using the Pareto distribution technique described in section 3.1. The dashed line represents the distribution obtained from the gravity model. In this case, 20% of the airports handle 60% of all the traffic. Pareto distributions are represented in solid lines. For example, the darkest line (with the steepest gradient) illustrates the case where the air taxi operator serves 5% (40 airports) of all available airports in the region.

In order to quantify the inequality of demand distribution a Gini Index was computed for each distribution. The Gini Index was computed as follow:

$$Gini \quad Index = \frac{\sum_{i=1}^{n} CTS_i}{(n+1)/2} - 1 \qquad (2)$$

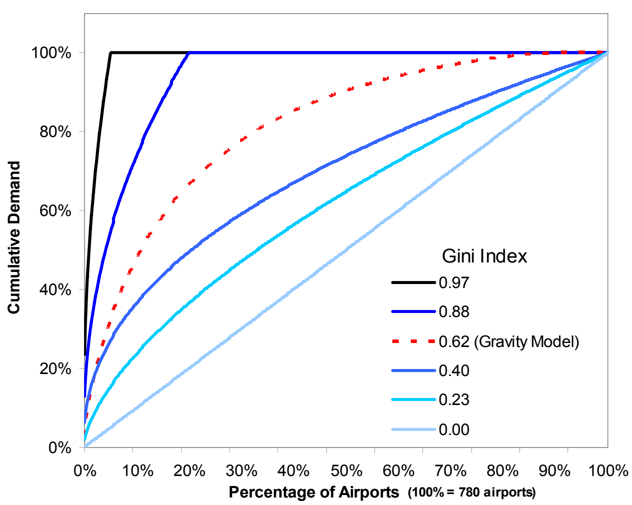

Figure 6 : Lorenz Curves of Demand

where CTS_i corresponds to the cumulative traffic share (from 0 to 1) for airport i and n corresponds to the total number of airports in the region. The Gini Index ranges from 0 to 1 where 0 means that the demand is uniformly distributed over the entire set of airports (e.g. for a set of 100 airports each airport would handle 1% of the overall demand) and 1 means that it is concentrated at two airports. The sensitivity analysis was performed for distributions from the two extreme cases.

Figure 7 shows the impact of the distribution of demand on the ratio of non revenue (repositioning) flight over revenue flight mileage. It should be noted that there is an asymptotic threshold for low Gini Indexes (uniformly distributed demand). This phenomenon is due to the fact that the network of airports, and by extension the average distance between any two airports, remains identical throughout the analysis. As the demand concentrates at certain airports, the number of repositioning flights decreases. This phenomenon forces the ratio of non revenue to revenue flight distances to decrease. This implies that the operations become more efficient. However, this behavior is not linear due to the structure of the network and the relative location of the airports where demand is concentrated. Close to maximum concentration, the value of the ratio drops sharply, to the point where no repositioning flights occur (when all the traffic is performed between two airports). This is an illustration of the operating scenario of scheduled commercial aviation where all the flights are revenue flights between a small number of airports. In this case no repositioning flight occurs. From a network design stand point, these results imply that there is a trade off between the efficiency of the operations and the size of the network. Early in the development of air taxi networks when fleets are limited in terms of size, there are incentives to concentrate the operations on a restricted set of airports in order to capture those efficiency gains. Later, when densities of aircraft increase the operations can be spread to a wider set of airports.

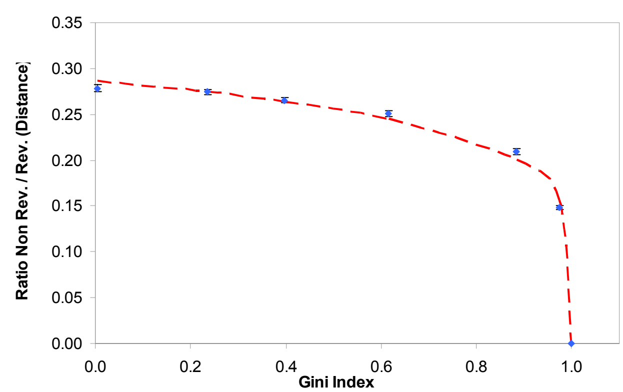

Figure 7: Sensitivity of the Ratio Nonrevenue / Revenue Flight Distances

Figure 8 shows the result of the same analysis on the number of revenue flights per day. As the concentration of demand increases, repositioning (non revenue) flights diminish and the fleet utilization becomes more efficient.

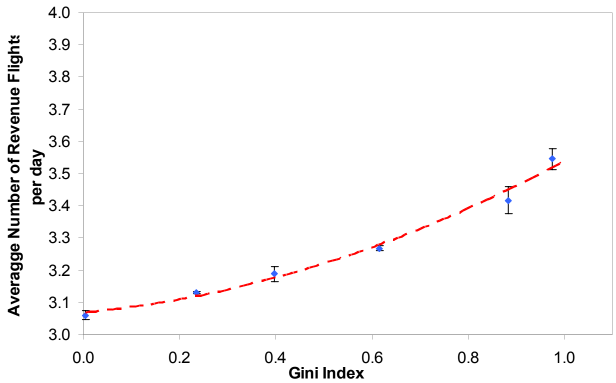

Figure 8: Sensitivity of the Number of Flight per Day

The Gini Index of the gravity demand model was found to be equal to 0.62. As a comparison, the Gini Index of existing Light Jets (Cessna CJ1, CJ2, Hawker 400, Learjet 31/35) was found to be equal to 0.86 (Bonnefoy 2005). This implies that the operations of existing Light Jets are more concentrated than what was assumed in the gravity model. This indicates that the simulations based on the gravity model are conservative compared to the concentration of actual demand patterns performed by existing jets with similar performance. As a reference, the Gini Index of scheduled commercial aviation is equal to 0.99 (over the same network).

4.1.3 Influence of Network Size

The decisions involving the deployment of air taxi operations over a network of airports require an assessment of the impact of network characteristics on the fleet performance. The design of the network is a variable over which air taxi operators have control and therefore be included in the strategies for market entry and growth.

The simulation based sensitivity analysis that was performed using networks with various sizes was found to be insightful. Figure 9 shows the results of a study of 4 networks with different sizes (from 400 to 700 miles around a core metropolitan area). For this example, a fleet of 75 aircraft and a constant level of demand for each network were used.

It was found that expanding a network led to an increase in the average daily revenue mileage and a decrease in the number of flights per day per aircraft. This is the result of the generation of flight requests with longer stage length when networks expand. In addition, the ratio of non revenue to revenue flight distances remains constant with an increase in network size. Even though the revenue mileage increases there is no significant efficiency improvement since repositioning flights also have longer stage lengths. From a deployment strategy stand point, this analysis shows that the performance of the fleet are less sensitive to the size of the networks than they are to the concentration of demand over these networks.

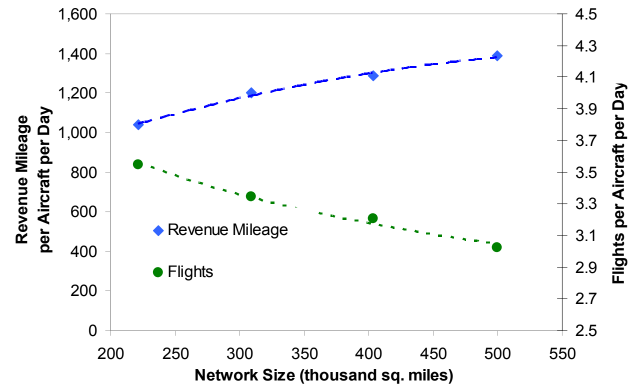

Figure 9: Sensitivity of Revenue Mileage and Number of Flights (per Aircraft per Day) to Network Size

4.2 What-If Scenario Analyses

The simulation based sensitivity analysis was an effective method for understanding the behavior of air taxi networks and for defining its acceptable envelope of operations. In addition to this analysis, what-if scenario analyses were performed. The simulation output provided numerical measures of the impacts of a specific scenario. This simulation tool was used to answer several challenging tactical questions and assess the impact of:

- using one versus multiple maintenance bases (infrastructure investment/deployment problem),
- adding a base to an expanding network,
- expanding an existing network to a new region (deployment problem),
- starting operations at a new sub network,
- increasing the density of the fleet in a network versus opening a new network (resource allocation problem),
- merging multiple regional networks and opening demand with origin and destinations in separate networks.

5 CONCLUSIONS

Air taxi networks are complex systems. Their complexity arises from the size of the fleet and the network (hundreds of aircraft and many thousands of airports served). But the size and spatial components of complexity are augmented by the dynamic nature and the low level of structure of the networks. Unlike scheduled commercial airlines that operate a fixed network (in the medium term) with schedules that are repeated week after week, the air taxi concept is based on un-structured networks driven by individual demand, therefore evolving continuously. This inherent complexity, the coupling of constraints and the nonlinearity of performance metrics were indications that aggregate models could not be applied.

The development of a fast-time simulator allowed an in-depth understanding of the potential behavior of large fleets of air taxi aircraft. The analysis of the output of single simulations gave the assurance that performance expectations were achievable based on reasonable input. The sensitivity analyses resulting from large number of simulation runs helped to define envelopes of operations where the performance metrics were acceptable. They also allowed gaining understanding of the behavior of the fleet at boundary conditions. Finally, the simulation tool was found to be useful in quantifying the impact of strategic or tactical decision through what-if scenario analyses. These analyses would have been costly to perform without the use of simulation. Fast-time simulation has proven to be an effective tool in the top down design approach of air taxi enterprises.

ACKNOWLEDGMENTS

The author would like to acknowledge Dr. Daniel Leblanc, former professor from the Department of Mathematics and Industrial Engineering at Ecole Polytechnique de Montreal in Canada, for his help and advice that was fundamental to the development of the simulator.

The author would also like to thank the early members of POGO Jet Inc. (formerly iFly Air Taxi), David Leblanc, Don Burr, Cameron Burr, and Mike Bristow for their input and feedback.

REFERENCES

Bonnefoy, P. 2002. *Prototype of an aircraft assignment and routing software for fleets of air taxi aircraft*, Ecole Polytechnique de Montreal, Canada.

Bonnefoy, P., Hansman, J., 2004. *Emergence and Impact of Secondary Airports in the United States*. American Institute of Aeronautics and Astronautics, ATIO6497.

Bonnefoy, P., Hansman, J., 2005. *Light Jets Operating Patterns in the Domestic U.S.*, NASA/FAA Joint University Program, January 2005.

Clarke, J.-P., 2004. *MIT Extensible Air Network Simulation (MEANS)*, Agifors Airline Operations 2004 Conference Proceedings.

FAA Office of Aviation Policy & Plans, 2005a. *Aerospace Forecasts Fiscal Years 2005-2016,* available online http://apo.faa.gov/forecast05/Forecast_for_2005.htm.

FAA, 2005b. *Federal Aviation Regulations and Policies,* available online http://www.faa.gov/regulations_policies/faa_regulations/carriers_operators.

Lee, L., Huang, H. et al., 2003. *Discrete Event Simulation Model for Airline operations: Simair*, Proceedings of the 2003 Winter Simulation Conference, 1656-1662.

Klein, A., 2000. *Fast-Time Simulation: A powerful Planning and Decision Support Tool for Airlines*, Handbook of Airline Operations, First Edition, Aviation Week.

Long, D., Lee D., et al., 2001. *A Small Aircraft Transportation System (SATS) Demand Model*, NASA/CR-2001-210874.

Sweet, D., and Manikonda, v., 2002, *Fast-time simulation for analysis of advanced air transportation concepts,* AIAA Modeling and Simulation Conference, 5–8 August 2002, Monterey, California.

US Census Bureau, 2000. *U.S. 2000 Gazetteer,* (available at http://www.census.gov/geo/www/gazetteer/places2k.html.

AUTHOR BIOGRAPHY

PHILIPPE A. BONNEFOY is a graduate student in the Engineering Systems Division (ESD) at the Massachusetts Institute of Technology. He is currently conducting research under the supervision of Prof. R. John Hansman at the International Center for Air Transportation at MIT. His current research activities focus on the Very Light Jet enabled Air Taxi Industry and its integration in the National Air Transportation System. He holds a Master of Science from the Department of Aeronautics & Astronautics at MIT and a bachelor in Aerospace Engineering from Ecole Polytechnique de Montreal in Canada. In 2003, he developed the Air Taxi Network Simulator. E-mail address: bonnefoy@mit.edu.