Investigation of Future Air Taxi Services Using Discrete-Event Simulation

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Abstract—This work conducts an analysis of the marketing and logistical considerations of an air taxi service using a discrete-event simulation. The air taxi service consists of a small fleet of aircraft transporting passengers on-demand within a regional network of cities. The discrete-event simulation models airports, passengers, aircraft, and an aircraft dispatcher. The study conducted attempts to answer the following questions: What effects will aircraft capacity or fleet size have on system performance? What effects will additional service have on system performance? A factorial experiment revealed: increasing aircraft capacity increases passenger wait times; and increasing the number of cities served increases the passenger wait times, number of flights, number of deadheads, and aircraft utilization rates.

I. INTRODUCTION

As major U.S. hub airports and their surrounding airspace become saturated approaching capacity, research spurred by NASA and the FAA’s Small Aircraft Transportation System (SATS) has focused on using air taxi services to alleviate congestion by shifting passenger traffic to underutilized airports. In this concept, an air taxi service transports passengers regionally on an on-demand basis using aircraft with limited seating capacity (such as less than ten passengers). Technologies required for a successful implementation of SATS, such as very light jets (VLJ), are just now becoming available; the FAA has projected that 4,500 VLJs will be in service by 2010 [4].

For new air taxi services to become a reality, the financial investment must meet investors’ expected rates of return. Thus, research, such as studies conducted by the Research Triangle Institute, has investigated what operational considerations are critical to economically viable air taxi services [5], [6].

Many factors related to service marketability and viability must be considered by air taxi service operators. For example, given that such a service cannot fly everywhere, which airports and routes should be served? The airports would need to be near a popular origin or destination and be easily accessible to ensure adequate passenger demand. The routes served must also remain within a region, such as city pairs no more than 350 miles distant. Marketers need to consider how the pricing scheme and reservations for an on-demand service might work. What time frame should an on-demand service support? What would be an acceptable maximum wait time if a passenger shows up and wants an immediate flight? Should the passengers be flown immediately or within an hour or two of them arriving at the airport?

Air taxi operators have many logistical decisions to make in support of marketing decisions. There are many different types of aircraft dispatching methods that could be used. The dispatch could be purely responsive (just dispatch an aircraft when a confirmed passenger requests service) or it could attempt to be predictive by placing aircraft at specific airports at a time when it is expected that passengers would be requesting service. The dispatch method directly affects the number of deadhead flights during a period of operation. Deadheads occur when an aircraft flies empty for the purpose of relocation. There are no revenue passengers, so the cost of the flight crew’s time and fuel burned by the aircraft is not being subsidized. Operators must also consider what type of aircraft to use, large capacity or small.

When considering aircraft capacity, there is an inherent tradeoff. Clearly, a large aircraft can carry more passengers, but usually at a higher operating cost. In periods of low demand, larger aircraft may not be profitable. Along the same lines, operators must decide how many aircraft should be maintained in the fleet. If there are too many aircraft in the fleet, the aircraft utilization rate could be too low and therefore the return on investment is poor. Each aircraft has certain fixed costs that must be covered. Aircraft hull-insurance, storage fees, scheduled maintenance, and lease or loan payments are just a few of the fixed costs associated with owning an aircraft. If the fleet is so large that most aircraft are not generating much revenue, then the air taxi service would not be profitable. Conversely, if the fleet or aircraft size is too small, then there could be unsatisfied demand resulting in a profit opportunity loss and a poor company perception.

In order to investigate some of these considerations, a discrete-event simulation was developed. This simulation model provides a tool to analyze the effects of marketing and operational decisions on the performance of an air taxi service. Whereas almost every marketing or operational consideration listed could be the focus of extensive study, two specific questions are addressed in this work. What effects will aircraft capacity or fleet size have on system performance? What effects will additional service (more
cities served) have on system performance?

II. AIR TAXI SERVICE MODEL

The air taxi service considered for this work operates within a SATS domain in support of the nationwide air transportation system. The study conducted looks at one air taxi service provider operating within this network of cities transporting passengers point-to-point on nonstop flights. It consists of a small fleet with a fixed number of aircraft serving a regional network of airports.

It is also assumed for this work that the air taxi service provider transports only unscheduled passengers. There are no scheduled flights for which passengers can make reservations and no priority is given to passengers beyond how long they have waited for service. Instead, it is assumed that passengers will arrive at a city requesting transport to a destination within the regional network. There will be one gate at the airport for each destination served by the air taxi service. Passengers will proceed to the appropriate destination’s gate and wait for departure. When there are enough passengers waiting to fill an aircraft, or if at least one of the passengers has been waiting for a minimum of one hour, the next available aircraft will be dispatched to the gate. Once the aircraft arrives, the passengers will then enplane and be transported to their destination.

III. DISCRETE-EVENT SIMULATION

The discrete-event simulation models four main objects: airports, passengers, aircraft, and an aircraft dispatcher. Airports in the simulation are equidistant from each other and it is assumed that each airport will have dedicated gates for each destination it serves. If airport (A) has destinations (B) and (C), then all of the passengers for (B) will depart from one gate and all of the passengers for (C) will depart from another.

The passengers enter the simulation according to a stationary arrival rate for each node in the regional city network. This arrival rate corresponds to a given demand for service at a particular city and is assumed to remain constant regardless of the number of destinations offered from each city (i.e. if a new destination choice is added, the arrival rate at the origin is unchanged, but some of the passengers arriving to the origin city are allocated to the new destination).

The logic for on-demand service is captured at the airport departure gate. Once at least one passenger has waited a minimum of one hour, or enough passengers are waiting at the gate to fill an aircraft, the passengers are ‘batched’ together and become a flight. This batch of passengers will then wait for the first available aircraft to come and pick them up for transport. This design means that aircraft capacity, in this work, is modeled in the on-demand logic when the passengers are batched together as a flight. Aircraft capacity is the level at which passengers are batched. So, the aircraft capacity is simply a number of passengers allowed to wait before batching.

The aircraft are assumed to always be available for service with no maintenance downtimes. Aircraft exist in the system with two states, busy and not busy. A busy aircraft is either currently transporting passengers or is relocating to transport passengers (deadhead flight). When the aircraft is not busy, it sits idle at the last node in the regional city network to which it transported passengers.

An aircraft dispatcher is not explicitly modeled in this simulation. The discrete-event simulation has built-in logic to allocate the aircraft using a specified dispatch method. The dispatch method for this work allocates aircraft according to a shortest distance rule. When a batch of passengers requests transport, the closest available aircraft will be allocated.

Several parameters can be easily changed in the simulation whereas other factors require modifications to the simulation model. In this model, passenger demand is determined at the origin and the simulation assumes that it is equally split between the possible destinations. The average amount of time between passenger arrivals at each city is set using a random number drawn from one of several pre-specified probability distributions. These probability distributions are easily modified by the analyst. In this work, an exponential distribution was used to generate passenger interarrival times.

Other parameters easily modified are: air taxi fleet size, aircraft initial positions, aircraft capacity and aircraft speed. These all are either explicitly specified by the analyst or randomly assigned by the simulation at the beginning of a simulation run. For the purposes of this work, the aircraft speed was set to 300 knots to reduce variance in the output metrics. The aircraft initial positions were explicitly set to the same origin cities for each run.

The final input to consider is the network structure. The number of nodes in the city network can be varied as well as the arc lengths (distances between cities). While the number of nodes can be varied, it is not easily changed in this simulation model because each node and its accompanying structures must be individually hard coded. For this work the simulation structure has either two or three nodes. To change the number of nodes from two to three, the demand at one of the nodes was set to zero (there were no passenger arrivals at that city) and the node was deleted as a destination choice at the other two nodes. Thus, passengers were only traveling between two nodes.

The main output that the simulation provides is a sample trajectory, or history, of one week of the air taxi service’s operation. From this sample trajectory, several derivative sample path statistics can be derived:

- Mean passenger interarrival times
- Average number of passengers served
- Average passenger wait for batch time (Amount of time passengers wait before they are batched – 1 hour elapsed or aircraft capacity is met)
- Average passenger wait allocate time (Amount of time that batched passengers wait for the allocated aircraft)
- Average passenger total time in the system
- Mean flight time (flight time is constant in this model)
- Average aircraft utilization (ratio of time the aircraft is busy divided by the time the aircraft is available)
- Number of revenue flights
A commonly used statistical formula, the equation below, was used to determine the number of replications to run for each scenario.

\[ n = \left( \frac{2 \cdot z_{\alpha/2} \cdot s}{w} \right)^2 \]

Where \( s \) is the sample standard deviation, \( w \) is the confidence interval width, \( z_{\alpha/2} \) is the Gaussian statistic for confidence level \( 1 - \alpha \), and \( n \) is the number of replications to use. An exploratory simulation was run with 10,000 replications of one week of air taxi operation to get stable point estimates for the output metric standard deviations, \( s \), and means. Using these stable point estimates, \( n \) was calculated for each output metric of interest. Of the various \( n \) values, the supremum was selected as the number of replications to use for each scenario and was calculated to be 1,400.

D. Apparatus

This simulation was developed using Rockwell Software’s Arena software package [7]. It is a graphical user interface built on top of the simulation language SIMAN. Arena provides many capabilities for collecting output statistics. However, for this simulation, statistics collection was coded into the model to save on computation time. The output statistics were streamed to an output file, and then analyzed using R [1], an open-source software environment for statistical computing and graphics.

Arena presented a slight modeling difficulty in dealing with its representation of aircraft. Arena has built-in functionality to represent an aircraft called a transporter. However, the transporter is only able to transport one entity at a time. For this simulation, the entities being transported are the passengers. So, to have a flight with multiple passengers on board, the passengers had to be ‘batched’ into a single batched entity for transport. The reason that the service model specifies two different conditions necessary for departure (1 hour wait time or aircraft capacity is met) is an artifact of this batching problem in Arena. If a constant batch size was set, for example at the aircraft capacity, depending on arrival rate, passengers would have to wait for longer than the on-demand service model expects. In order to work around this batching rigidity in Arena, the passengers are batched for a flight when either the number of passengers waiting is equal to the aircraft capacity, or if one passenger has been waiting for at least one hour.

V. RESULTS

A. Model Implementation Results

It took the analyst four hours to run the model and gather all of the data for the factorial experiment. The total computation time required for the simulation to generate the data was 35.03 minutes with an average of 1.09 minutes per scenario. Total computation time for the post-data processing using R took 13.57 minutes with an average of 0.42 minutes per scenario. Most of the analyst’s time for conducting the experiment was spent setting up each simulation scenario and ensuring that the correct parameter values were used.
### TABLE III
DESCRIPTIVE STATISTICS, ALL PARAMETERS LOW AND HIGH

<table>
<thead>
<tr>
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<th>Low Scenario</th>
<th>High Scenario</th>
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<tr>
<td><strong>Mean</strong></td>
<td><strong>S.D.</strong></td>
<td><strong>Mean</strong></td>
</tr>
<tr>
<td>TotalTime</td>
<td>1.065</td>
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</tr>
<tr>
<td>WaitBatch</td>
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<tr>
<td>WaitAllocate</td>
<td>0.044</td>
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<tr>
<td>Flights</td>
<td>113.198</td>
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<tr>
<td>Deadheads</td>
<td>23.125</td>
<td>4.444</td>
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<tr>
<td>Passengers</td>
<td>169.648</td>
<td>12.905</td>
</tr>
<tr>
<td>Utilization</td>
<td>0.081</td>
<td>0.005</td>
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</table>

An investigation of the data revealed some unrealistic wait times for aircraft allocations, which is the amount of time that batched passengers wait for an available aircraft to come transport them. For some replicates, the average aircraft allocation wait time was six hours which was unexpected for even the largest city distance. The wait time should have been at most a few minutes more than the travel time between nodes in the regional city network.

The analyst wanted to model an on-demand air taxi service provider and have no passenger total time in the system longer than about two hours. A lack of a prioritization scheme in the built-in Arena dispatch method caused one city to be consistently overlooked. The particular scenarios that were generating the highly skewed aircraft allocate wait times had city distance at the high level, number of cities at the high level, passenger arrival rate at the high level, and number of aircraft at the low level. This created a situation in which the demand exceeded the system’s capacity. Thus, there were always passengers waiting for transport whenever an aircraft completed a trip and one city was continuously overlooked.

Because of project scheduling constraints, there was insufficient time to implement a custom dispatch method, so the built-in Arena method was used. Therefore, city distance, was removed from the experimental design. All of the data for city distance at the high level were removed (including the unrealistic wait time data) and the experimental design was changed into a four factor design.

#### B. Empirical Results

Table III lists the descriptive statistics of the response variables for the scenario when all of the factors are at their low levels, and the scenario when they are all at their high levels. There is clearly a difference between the numbers of passengers served for the low scenario versus the high scenario. This is because the baseline scenario has a low passenger arrival rate compounded with the fact that there is one less origin from which passengers enter the system. It is interesting to note that the \( \text{WaitBatch} \) time is lower for the high scenario than the low scenario. This is because there is a higher arrival rate in the high scenario, making it more likely that no passenger will wait for an hour before a batch is created. While the aircraft utilization is much lower for the low scenario than for the high scenario, neither scenario causes a very high utilization rate. The deadheads are driven by the passenger demand and the wait batch model logic.

![Fig. 1. Side-by-side box-and-whisker diagrams of the effect of the aircraft capacity on each response variable.](image)

Table IV contains ANOVA results for all of the response variables. For many of the responses, all factors and interactions showed significance. \( \text{Flights} \) showed no significance with any factor or interaction including \( \text{NumAC} \) because the number of flights are dependent only on the passenger demand, which is controlled by the interarrival rate, number of cities, and the model’s on-demand logic. The number of passengers served is dependent only on the number of cities and interarrival rate, so it is reasonable that \( \text{InterArrival}, \text{NumCities} \), and their interaction shows significance. \( \text{WaitBatch} \) is only dependent on the passenger arrival rate and \( \text{CapacityAC} \). \( \text{NumCities} \) is significant here, because it is actually affecting the passenger arrival rate at an airport’s departure gate and will be further explained later.

The dataset gathered from the experiment was used to answer the operational question: What effects will result if the air taxi service adds more resources (larger aircraft capacity, larger aircraft fleet size)? From the ANOVA table, it appears that aircraft capacity has a significant effect on all of the response variables measured except for number of passengers. It makes sense that the number of passengers would not be affected by the aircraft capacity, since the number of passengers is solely dependent on the number of cities and the passenger arrival rate. From the ANOVA table and Fig. 1, it is clear that \( \text{CapacityAC} \) has a significant effect on every thing except for \( \text{Passengers} \).

Larger aircraft capacity increases the passenger total time in system and amount of time that batched passengers wait for an available aircraft to come transport them, \( \text{WaitBatch} \). This makes sense, because \( \text{WaitBatch} \) is
The ANOVA table and Fig. 2 show significant effects of fleet size with number of deadheads, passenger total time in system, aircraft utilization rate, and the amount of time passengers must wait for an aircraft to become available to transport them, WaitAllocate. Increasing the number of aircraft decreases a passenger’s total time in system, likely because of the decrease shown in the variable WaitAllocate. When there are more aircraft in the fleet, it will be more likely that an aircraft is immediately available to transport passengers. The number of deadheads is decreased because when passengers are ready to depart, it is more likely that an aircraft will be idly waiting at the same airport. Accordingly, aircraft utilization rate is decreased as the fleet becomes larger, because the aircraft will more frequently be idle.

The second question examined for this work is: What effects will more service (adding cities to the regional network) have? The ANOVA table and Fig. 3 show that the number of cities has a significant effect on all of the response variables measured.

Table IV

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<tr>
<th>Source of Variation</th>
<th>DH</th>
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<th>PA</th>
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<td>InterArrival</td>
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Fig. 2. Side-by-side box-and-whisker diagrams of the effect of the number of aircraft on each response variable.

The passenger total time in system is increased because included in passenger total time in system, and passengers will have to wait longer (closer to the one hour maximum) at a gate for more people (higher aircraft capacity) to arrive at a gate. The number of flights and deadheads are decreased when aircraft capacity is increased because it will take fewer flights to satisfy a given demand, and fewer flights will result in fewer deadheads. Increasing the aircraft capacity decreases the aircraft utilization because the aircraft is not flying as frequently as when the capacity is smaller.

The ANOVA table and Fig. 2 show significant effects of fleet size with number of deadheads, passenger total time in system, aircraft utilization rate, and the amount of time passengers must wait for an aircraft to become available to transport them, WaitAllocate. Increasing the number of aircraft decreases a passenger’s total time in system, likely because of the decrease shown in the variable WaitAllocate. When there are more aircraft in the fleet, it will be more likely that an aircraft is immediately available to transport passengers. The number of deadheads is decreased because when passengers are ready to depart, it is more likely that an aircraft will be idly waiting at the same airport. Accordingly, aircraft utilization rate is decreased as the fleet becomes larger, because the aircraft will more frequently be idle.

The second question examined for this work is: What effects will more service (adding cities to the regional network) have? The ANOVA table and Fig. 3 show that the number of cities has a significant effect on all of the response variables measured.

Fig. 3. Side-by-side box-and-whisker diagrams of the effect of the number of cities on each response variable.

The passenger total time in system is increased because...
both the wait time for aircraft allocation, \textit{WaitAllocate}, and amount of time that a passenger waits for an aircraft to be dispatched, \textit{WaitBatch}. \textit{WaitBatch} time increases as the number of cities increase, because demand is constant at each origin city. As more destination cities are added from an origin, the passenger arrival rate for each gate is reduced. Thus, more frequently, passengers have to wait closer to an hour before an aircraft is dispatched to transport them. The \textit{WaitAllocate} times increase because it is more likely that an aircraft will not be at the node of the requesting passengers. Thus, the passengers will have to wait for the aircraft to fly to them as a deadhead. This occurrence also explains why there are more deadheads when there are more airports in the regional network. Adding a new city increases the number of passengers, because a new node with new demand is being introduced to the system. This new demand also causes an increase in the number of flights which in turn increases the utilization of the aircraft. More demand increases the number of flights, which increases the aircraft utilization rate.

VI. DISCUSSION

While the air taxi service model used in this work is simple, the simulation still revealed some interesting system dynamics. Increasing the aircraft capacity increases the passenger wait times, while increasing fleet size decreases them. Increasing the fleet size also reduces the aircraft utilization rates. Increasing the number of cities served increases the passenger wait times, number of flights, number of deadheads, and aircraft utilization rates.

The number of deadheads is higher than one would expect due to the dispatch strategy and model’s on-demand logic. In this simulation, it is a frequent occurrence that an aircraft will drop passengers off at a destination and then depart this city as a deadhead when there are currently passengers waiting for departure to another city. These passengers are not yet batched, either because there are not enough waiting, or at least one passenger has not been waiting for at least one hour. The aircraft will not transport passengers unless they are batched. Instead, the aircraft will deadhead to another city to transport passengers that have already been batched and return to this city only once those passengers waiting have been batched. Thus, the model’s logic is inflating the number of deadheads. In a real world situation, an air taxi service would rarely pass up an opportunity to carry revenue passengers.

The simulation also does not make it easy to add cities to the network structure. Ideally, it would be simple to add cities or other complexities to easily determine their effects. The dispatch method proved to be problematic and may be a source for future work. Arena’s built-in dispatch method just is not appropriate for modeling this problem. An analyst-designed custom dispatch method will have to be employed if Arena is continued for use in this domain. A dispatch method using some optimization or demand prediction should be considered.

The air taxi service model used for this work does not account for aircraft maintenance downtimes, crew scheduling conflicts, adverse weather, non-stationary passenger arrival rates, pre-scheduled flights, competing modes of travel, etc. The model was kept parsimonious to ease model interpretation and computation. While the simulation may certainly have the capabilities to model the additional complexity, it is unclear how the additional complexity may confound effects or how much more computation time will be required to run it.

Given those limitations, it is still useful for other purposes. Lee et al. [3] used the simulation to calibrate and validate their mathematical flow model of the same simple air taxi service. The simulation brought deadhead flights to the research team’s attention as it was not something accounted for in their original mathematical flow model [2]. Future work will look to extend this model to perhaps address some of the additional complexities listed above. Future work should also include some measure of how full an aircraft is in the aircraft utilization metric. This addition could provide some more useful and interesting insights into the air taxi service’s operations.

REFERENCES