Development of an Airport Choice Model for General Aviation Operations

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The National Aeronautics and Space Administration (NASA) is developing an “enhanced general aviation aircraft” called the Small Aircraft Transportation System (SATS). The aim of NASA is to harness developments in aircraft engine and airframe technology, communications, and navigation to produce a new type of vehicle with near all-weather operations capability and the ability to use airports with minimally equipped landing facilities as described in the SATS program plan (1). NASA expects SATS to fill a niche in the medium- to long-distance transportation market by reducing travel times and increasing the level of utilization of the general aviation (GA) airport network in the United States.

As a first step in assessing the feasibility of deploying SATS, the U.S. Congress mandated NASA to prove four technical capabilities:

- Improve lower landing minima,
- Allow high-volume operations at nontowered airports,
- Improve single pilot safety, and
- Allow the seamless integration of aircraft into the enroute airspace system.

Although the above capabilities may be proven by developing the appropriate technology, it is also necessary to estimate the level of demand for the new transportation mode and its impact on the National Airspace System (NAS). The airport choice model was developed as part of a multistep modeling process in an analysis of intercity travel demand (2). The process (usually referred to as the four-step model) includes four major stages: trip generation, trip distribution, mode choice, and trip assignment (illustrated in Figure 1). The methodology for each step is basically the same as the one used in urban transportation demand analysis, except for trip assignment.

An intercity GA trip involves three subtrips:

- Access to an origin airport,
- Flight between origin and destination airports, and
- Egress from the destination airport to the final destination.

To capture these subtrips during the trip assignment process, an airport choice model that assigns GA travelers to airports is needed. Using GA demand in the form of region-to-region passenger flows obtained from the mode choice step, the model estimates airport-to-airport passenger flows. The airport choice model introduced in this paper also includes an internal procedure that converts airport-to-airport passenger flows to airport-to-airport aircraft flows by GA aircraft type. The task can be stated more formally as follows: given GA travelers $t_{ij}$ originating from the center of region $i$ and ending at a center of region $j$, find the most likely origin and destination airport pair ($k$ and $l$) and the most likely GA aircraft type $m$ selected by the travelers.

A substantial amount of research and study have been conducted to investigate the behavior of air travelers selecting airports for travel. However, these studies focus mainly on identifying factors that influence commercial airline travelers’ choices of origin and destination airports. For GA operations, no credible database or means of predicting traffic flows between airports in the United States is available. This paper gives an overview of an airport choice model for GA travelers that can be used to estimate the demand for GA operations between selected airports given initial GA travel demand between U.S. regions.

In the next section, the previous studies conducted in the same context are reviewed. Then, detailed procedures are presented along with basic assumptions for the suggested methodology. Subsequently, the input data required for the model and a calibration procedure for the model are described. Finally, some computational results from the model are presented with some recommendations.

PREVIOUS STUDIES ON AIRPORT CHOICE MODELS

Random utility models formulated as logit or probit models have been widely used in models of airport choice (3). These random utility models were originally developed in economic theory to study...
consumer choice on the basis of "disutilities" associated with a set of alternatives. Teodorovic and Vukanovic (4) have applied fuzzy logic techniques using linguistic variables to capture the uncertainty of the traveler's behavior in models of transportation mode and route choice.

Using logit models, Kanafani et al. (5) and Hansen (6) studied the airport selection behavior of commercial airline travelers when choosing a departing airport in San Francisco Bay area. Similar studies were conducted by Skinner (7) and Windle and Dresner (8) in the Washington, D.C.–Baltimore, Maryland, area and by Augustinus and Demakopoulos (9) in New York City. Outside the United States, Ashford and Benchemam (10) conducted similar studies for airports in Britain; Innes and Doucet (11) for airports in rural New Brunswick, Canada; and Furuichi and Koppelman (12) for four major airports.
in passengers. Generally, these studies have tried to estimate the fraction of passengers captured by competing airports within the same metropolitan area. A literature review reveals that the logit model is the predominant technique used in modeling airport choice. The variables most frequently used in the utility function of the models are access cost (measured as time or distance) and flight frequency. Lunsford and Gosling have produced a comprehensive review of airport choice and ground access choice models (13).

Most airport choice models developed to date concentrate on commercial air travel and are regional in scope. Few have attempted to model GA travelers’ airport choice behavior. One of the major constraints facing GA operations modeling is the lack of detailed and reliable data about GA trips. Even so, a few GA airport choice models have been developed in the past.

Ghobrial applied a regression model to forecast aircraft operations at GA airports, using both socioeconomic variables (e.g., population and employment) and supply variables related to the airport (e.g., runway length, presence of control towers, and presence of charter flights) (14). GRA, Inc., developed another regression model for estimating GA operations at nontowered airports using towered and nontowered airport data (15). The model incorporated both socioeconomic variables (e.g., income per capita and county-level nonagricultural employment data) and airport-specific variables (e.g., total number of aircraft and proportion of single-engine aircraft based at airports). A set of data from 232 airports was used to obtain regression parameters, and the developed model was applied to estimate GA operations at 2,789 GA airports.

The Logistics Management Institute (LMI) also developed an aircraft utilization model to generate demand at 2,865 U.S. GA airports (16). An initial attempt to develop an econometric regression model using population and average household income was abandoned because of low $R^2$ values and the difficulty of obtaining accurate GA data for all airports. Instead, the aircraft utilization model was developed using reported FAA regional utilization rates, landing rates, the number of aircraft in the region, and the number of aircraft based at each airport by aircraft type (single-, multiple-, and jet-engine aircraft). The model estimated approximately 11 million operations and 14 billion transported passenger miles for 2000.

Each of the techniques mentioned above was initially considered as a modeling approach for the GA airport choice model in this paper. However, the regression approach was avoided because of the difficulty of obtaining data for the independent variables both now and in the future. To calibrate a discrete choice model, an extensive survey would be required to assess GA traveler’s choice behavior in association with travel time and travel cost for each mode. It was not feasible to conduct a survey because of logistical, financial, and time constraints. Thus, the approach adopted was a gravity-type model formulation to distribute region-to-region passenger flows to the airports.

**MODEL DEVELOPMENT AND CALIBRATION PROCEDURE**

The GA airport choice model presented in this paper proceeds in three steps (illustrated in Figure 2):

1. Distribute the GA trips estimated in the mode choice process to airports in the database.
2. Split the trips from the airports into person trips by aircraft type.
3. Convert the person trips by aircraft type into aircraft operations.

In the mode choice stage of the four-step process illustrated in Figure 1, a stratified diversion curve was developed to split the output of the trip-distribution process into person trips by three modes: commercial aviation, GA, and other (2). Each trip category was further separated into business and nonbusiness travelers for each mode. However, the output for GA business and nonbusiness trips was combined and used as input to the airport choice model.

**Trip Distribution (Pseudogravity Model)**

In converting the intercounty person trip table (3,091 × 3,091 matrix) to GA aircraft operations between airports, a model based on principles similar to the gravity model (a synthetic model analogous to Newton’s law of gravity) used in trip distribution was embedded in the GA airport choice model. Used extensively in travel demand modeling as a trip distribution tool (17), the gravity model is expressed mathematically as

\[ T_{ij} = k \frac{P_i}{W_{ij}} \]  \hspace{1cm} (1)

where

- $T_{ij}$ = trips between zones $i$ and $j$,
- $k$ = a constant,
- $P_i$ = trip production from origin zone $i$,
- $A_j$ = attractiveness of the destination zone, and
- $W_{ij}$ = impedance between zones $i$ and $j$.

The underlying assumption of the model is that for a given volume of trips from an origin zone $i$, the proportion of trips attracted to a destination zone $j$ is positively correlated to the trip production and attractiveness of the origin and destination zones, respectively, and negatively correlated to distance between the zones. The attractiveness variable can be quantified as population, number of shopping centers, or some such. Depending on the scenario being analyzed, the impedance can be represented as cost or drive time. The model has evolved to a more general form:

\[ T_{ij} = P \sum A_i F_j K_{ij} \]  \hspace{1cm} (2)

where $F_j$ is a travel time friction factor and $K_{ij}$ is a socioeconomic adjustment factor.

In the pseudogravity model formulation used in the GA airport choice model, the origin county serves as the origin zone (from which trips emanate) and the sets of airport pairs associated with each origin–destination county pairs as destinations (to which trips are distributed). For an origin county $i$ with $K$ nearby airports and a destination county $j$ with $L$ nearby airports and given GA travelers between the counties $t_{ij}$, the number of GA travelers between counties $i$ and $j$ via specific airports $k \leq K$ and $l \leq L$, $T_{ij}$ is given by

\[ T_{ij} = t_{ij} \times \sum_{k=1}^{K} \sum_{l=1}^{L} A_{ijkl} \]  \hspace{1cm} (3)
where $A_{ijkl}$ is an attractiveness factor of the route for trips between counties $i$ and $j$ via airports $k$ and $l$. The attractiveness factor $A_{ijkl}$ is further defined as

$$A_{ijkl} = \frac{ABsd_{ik} \times ABsd_{jl} \times RD_{ijkl}}{\alpha_1 \times \alpha_2}$$  \hspace{1cm} (4)$$

where $\alpha_1$ and $\alpha_2$ are model parameters to be calibrated and $ABsd_{ik}$ and $RD_{ijkl}$ are the aircraft-based factor and the relative distance for a given trip between counties $i$ and $j$ via airports $k$ and $l$, respectively.

In Equation 4, it is assumed that the attractiveness of an origin-destination pair of airports serving an origin-destination pair of counties is positively correlated with the number of aircraft based at the airport pair and negatively correlated to the relative distance. The two factors defining $ABsd$ and $RD$ are given by

$$ABsd_{ijkl} = ABsd_{ik} \times ABsd_{jl}$$  \hspace{1cm} (5)$$

where $ABsd_{ik}$ and $ABsd_{jl}$ are the number of aircraft based at the airports $k$ and $l$ serving origin and destination counties $i$ and $j$, respectively, and
Aircraft utilization and occupancy factors were obtained by an adjustment where

\[ RD_{ij} = \frac{\text{intcounty}_{ij}}{\text{accessdist}_{ik} + \text{egressdist}_{jl} + \text{intair}_{kl}} \]

The formulation of the pseudogravity model in Equation 3 is based on an underlying assumption that travelers faced with a choice of different routes prefer the route with the shortest travel time and the airport with the greatest volume of travel services (e.g., number of aircraft based at the airport or frequency of trips to destination).

To a limited extent, the model seeks to mimic the effects of access time, access distance, and flight frequency (level of service) that have been identified in earlier studies. However, flight frequency is not relevant for GA airports because GA is an on-demand service. For this reason, flight frequency is replaced by the number of aircraft based at the airport.

The relative distance attractiveness factor aims at distributing more travelers to the shorter routes of selected county pairs. The airport attractiveness factor distributes more trips to origin–destination airport pairs that have more aggregate services.

The output from the gravity model is person trips between each airport in the database and is in the form of a 3,346 x 3,346 table (Figure 2).

**Splitting Person Trips (by Aircraft Type)**

The table of person trips between airports is further split by aircraft type. Factors used in splitting the trips between the aircraft types are the number of each aircraft type based at the airport, reported yearly utilization hours, occupancy values for the different aircraft types, and a trip distance distribution profile. The form of the expression used for the distribution is written mathematically as

\[ T_{ijkl} = T_{ij} \times \frac{\text{ABsd}_{ik} \times \text{ut}_{im} \times \text{occ}_{m} \times \text{Ddist}_m}{\sum_k \text{ABsd}_{ik} \times \text{ut}_{im} \times \text{occ}_{m} \times \text{Ddist}_m} \]

where

- \( T_{ij} \) = trips from county \( i \) to \( j \) through airport \( k \) and \( l \) using aircraft type \( m \).
- \( m \) = aircraft type (i.e., single, multiple, or jet engines).
- \( \text{ABsd}_{ik} \) = number of aircraft based at an airport \( k \) serving the origin county \( i \).
- \( \text{ut}_{im} \) = yearly utilization hours of the aircraft type \( m \).
- \( \text{occ}_{m} \) = average occupancy of aircraft type \( m \), and
- \( \text{Ddist}_m \) = a value obtained from the distance probability distribution for aircraft type \( m \) (the derivation of which is outlined below).

**Utilization and Occupancy Factors**

Aircraft utilization and occupancy factors were obtained by an adjustment of values derived from those reported in the General Aviation and Air Taxi Activity Survey (GAATA) (18). Table 1 shows the aircraft occupancy and utilization factors used in this analysis.

**Development of a Probability Density Function**

According to GAATA data, the U.S. civil GA fleet consists of about 185,000 fixed-wing aircraft: approximately 172,000 piston-engine aircraft, 6,000 turboprops, and 7,000 jets (18). Each of these aircraft groupings has different range and performance features that make them unique as modes of travel. Single-engine aircraft have typical cruise speeds ranging from 120 to 175 mph within a range of 500 to 1,200 miles; turboprops and multiple-engine aircraft cruise between 200 and 350 mph and have ranges of 600 to 1,500 miles. Turbojets have cruise speeds ranging from 400 to 600 mph (19).

As expected, overlaps in aircraft performance warrant the development of a stochastic model to assign trips generated by the airport choice model. Trip length clearly is a deciding factor in selecting aircraft type for a trip. The use of a distance distribution variable in the aircraft attractiveness seeks to account for this phenomenon. Generally, more jet aircraft are used for longer trips, and more single-engine types are used for shorter trips.

A Weibull distribution developed by LMI and George Mason University for the LIMNET–SATS model was modified and used in the analysis (16). The distribution was constructed by selecting 12 samples from FAA’s Enhanced Traffic Management System database (20), which contains flight plan information for instrument flight rules flights in the NAS. The data collected was approximated with a Weibull distribution. The form of the probability and cumulative density function can be expressed mathematically as

\[ f(x;\delta,\lambda) = \lambda x^{\delta-1} e^{-\lambda x^\delta} \quad x \geq 0, \; \delta > 0 \]

and

\[ F(x;\delta,\lambda) = 1 - e^{-\lambda x^\delta} \quad x \geq 0, \; \delta > 0 \]

where \( \delta \) and \( \lambda \) are the Weibull scale and shape parameters, respectively (16). The resulting equations for the single-, multiple-, and jet-engine aircraft types are Equations 10, 11, and 12, respectively:

\[ f(x;\delta,\lambda) = \begin{cases} \frac{1.15}{237} \left( \frac{x}{237} \right)^{0.15} e^{-\left( \frac{x}{237} \right)^{0.15}} & x \geq 0 \end{cases} \]

\[ f(x;\delta,\lambda) = \begin{cases} \frac{1.16}{289} \left( \frac{x}{289} \right)^{0.16} e^{-\left( \frac{x}{289} \right)^{0.16}} & x \geq 0 \end{cases} \]

<table>
<thead>
<tr>
<th>Aircraft Type</th>
<th>Average Occupancy (Persons)</th>
<th>Average Annual Utilization (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-engine</td>
<td>1.7</td>
<td>128</td>
</tr>
<tr>
<td>Multi-engine</td>
<td>2.4</td>
<td>170</td>
</tr>
<tr>
<td>Jet-engine</td>
<td>3</td>
<td>320</td>
</tr>
</tbody>
</table>

**TABLE 1 Aircraft Type Factors (used in deriving aircraft attractiveness)**
A plot of the modified Weibull distribution is shown in Figure 3. The aircraft split process yields three $3,346 \times 3,346$ airport-to-airport person trip tables for each aircraft type (Figure 2).

**Converting Person Trips to Aircraft Trips**

To assess the impact of aircraft operations at airports in the NAS, the airport-to-airport person trips were converted to aircraft operations by using average aircraft occupancy factors. The occupancy values used are shown in Table 1. The expression is written as

$$\text{ops}_{ml}^\text{m} = \frac{T_{ml}^\text{m}}{\text{occ}}$$

where $\text{ops}_{ml}^\text{m}$ is the aircraft operations for aircraft type $m$ from an origin county $i$ to a destination county $j$ through airport $k$ in origin county and airport $l$ in destination county.

The operations by aircraft type are one-way trips. A return-trip table is generated by adding the trips departing and arriving at each airport. The total aircraft operations can be obtained by doubling the number of return trips because it was assumed that all trips return to their originating counties. The output from this stage yields three $3,346 \times 3,346$ airport-to-airport trip tables of aircraft operations for each aircraft type (Figure 2).

**Model Calibration Procedure**

The model was calibrated by comparing estimated operations at towered airports from the model with those from the FAA terminal area forecast (TAF). This calibration accounts for only towered airports because the TAF statistics are in general not reliable for nontowered airports.

The model parameters to be calibrated are $\alpha_1$ and $\alpha_2$ (Equation 4). The model is initially run with a pair of starting values for the parameters. Then, the estimated aircraft operations at towered airports obtained from the model is compared with the reported itinerant operations from TAF data. The root-mean-square error (RMSE) is used to measure the goodness of fitness of the selected parameter values. The procedure is repeated for a range of pairs of values for the parameters $\alpha_1$, $\alpha_2$. The parameter values that provide the minimum RMSE are selected.

Using best parameter values, the model is run again to obtain the airport-to-airport person trip table. The final output is three $3,346 \times 3,346$ airport-to-airport tables of aircraft operations that serve as input for the network analysis stage of the GA transportation modeling process.

**Pseudocode for Airport Choice Model**

The outline of computations in the model follows.

- For $\alpha_1 = 0$ to 2 in increments of 0.01
- For $\alpha_2 = 0$ to 2 in increments of 0.01
  - For $i = \text{all counties}$
  - For $j = \text{all counties}$
    - For $k = \text{all airports around county } i$
      - For $l = \text{all airports around county } j$
        - Compute $\text{ABsd}_{ijkl}$
        - Compute $\text{RD}_{ijkl}$
        - Compute $A_{ijkl}$
        - Next $k$
        - Next $l$
      - Compute $T_{ijl}^m = t_\text{d} \times \sum_k A_{ijkl}$
      - Next $j$
      - Next $i$
    - Sum $T_{ij}^m$
    - Compute RMSE for towered airports
    - Save $\alpha_1$, $\alpha_2$, and RMSE ($\alpha_1$, $\alpha_2$)
    - Next $\alpha_1$
    - Next $\alpha_2$
  - Select best RMSE ($\alpha_1$, $\alpha_2$)
  - Run model again to estimate operations at airports.

**Variation of the Model**

As a variation of the model described, another version of the model was tested using itinerant operations instead of aircraft based at the airport as a factor defining the attractiveness. The estimated operations at towered airports obtained from both models were compared with the reported operations from TAF. The plots in Figure 4 show a reduction in the level of scatter around the 45° line, which represents the exact match. This result indicates the reported itinerant operations are a better variable than aircraft-based. Hence, it is the one used in current versions of the model.

**DATA PREPARATION**

**Airport–County Allocation**

The first stage in the model is to “distribute” travelers from the counties to the airports in the model. When selecting an airport, travelers choose from a candidate set of airports. To define the candidate set of airports, an influence area was defined for each county and airports within that area treated as the candidate set of airports for travelers from that county.
The influence area was defined as 120% of the equivalent county radius, which ensured that 98% of all airports in the model were considered as candidate airports of at least one county. The radius of the county is computed from the county area. In cases where there is no airport within the initial radius, the factor of 1.2 (i.e., 120%) is increased in steps by 0.1 until an airport is found. The output from this computational process is saved in an array and used in the main module.

Travel Distances

The access distances from each county to its candidate airports were computed and stored in a matrix. The intercounty distances between all counties were computed and stored as a $3,091 \times 3,091$ matrix. The interairport distances also were computed and stored as a $3,346 \times 3,346$ matrix. Other pertinent data such as the distance probability distribution, occupancy, and utilization factors related to the three aircraft categories also were prepared and saved in the database.

Centroids

The initial input to the model is an intercounty person trip table ($3,091 \times 3,091$) of GA trips from the centroid of each county. The county centroids used in the model are population-weighted, which are more realistic in transportation analysis than geographic centroids.
### TABLE 2  Model Output: Estimated Values by Aircraft Mode

<table>
<thead>
<tr>
<th>Aircraft Type</th>
<th>Average Stage Length (mi)</th>
<th>Total Hours Flown (thousands)</th>
<th>Total Trip Distance (mi, thousands)</th>
<th>Total Operations (thousands)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-engine</td>
<td>447</td>
<td>6,980</td>
<td>1,030,000</td>
<td>8,318</td>
</tr>
<tr>
<td>Multi-engine</td>
<td>587</td>
<td>2,760</td>
<td>759,000</td>
<td>4,776</td>
</tr>
<tr>
<td>Jet-engine</td>
<td>1084</td>
<td>1,210</td>
<td>652,000</td>
<td>2,302</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>10,950</strong></td>
<td><strong>2,441,000</strong></td>
<td><strong>15,396</strong></td>
<td><strong>15,396</strong></td>
</tr>
</tbody>
</table>

### Airways

The set of airports to be included in the model needed to be specified. The source of information on the airports was the *National Transportation Atlas Databases 2001* (NTAD; 21) compiled by the Bureau of Transportation Statistics from information provided by U.S. DOT and other federal administrations. NTAD lists 19,793 aviation facilities, including airports, heliports, balloon ports, glider ports, seaplane bases, short-takeoff and landing ports, and ultralight ports (21).

To perform an analysis for GA operations today and in the future, criteria have been developed to identify airports through which trips will be made. According to the FAA, on a normal day, 95% of aircraft in the U.S. fleet can be accommodated at airports with runway lengths greater than or equal to 3,000 feet (22). Three criteria were used in selecting facilities for the model:

- Airports designated as public use,
- Airports with paved runways, and
- Airports with usable runway length of more than 3,000 feet.

Airport and runway data sets were parsed from NTAD and merged into a single data set. It should be noted that runway information for the airports is for 1998, whereas the airport data set is for 2000.

Relevant fields extracted for each airport include the three-letter airport code, airport latitude and longitude, aircraft based at the airport by engine type (single, multiple, or jet engine), annual itinerant GA operations, and whether the airport is towered. It should also be noted that some of these airports did not have any based aircraft in any of the three categories. These airports were left in the final data set because as GA and SATS traffic grows, there could be some future activity at these airports. The final airport set contained 3,436 airports.

### COMPUTATIONAL RESULTS

During the calibration stage, the model was run for $\alpha_1$ and $\alpha_2$, each running from 0 to 2 with a step size of 0.1. The minimum RMSE was obtained for values of 0.8 and 0 for $\alpha_1$ and $\alpha_2$, respectively. Because $\alpha_1$ is associated with the attractiveness factor related to aircraft based at airport and $\alpha_2$ is related to the relative distance factor, the current form of the model implies that the choice of trip makers is more sensitive to the aircraft based at airport attractiveness factor than to the relative distance factor.

Table 2 is a summary of total aircraft operations estimated from the model. The results indicate higher trip volumes for single-engine aircraft (as expected) than for the two other aircraft types. Nevertheless, jet aircraft show some gain in the number of total operations and flights.

An inspection of the distance distribution reconstructed using aircraft operations estimated by the model shows a profile and shape fairly close to the theoretical Weibull distribution used to split the trips by aircraft type. Although irregular, the shape of the jet operations curve can be attributed to insufficient data points because relatively few (15%) GA trips are made using that aircraft type. The distributions (Table 2) show that expected travel distances are 447, 587, and 1,084 nautical miles for single-, multiple-, and jet-engine aircraft, respectively. Figure 5 is the model-derived probability density function for aircraft operations.

From the person trip tables and the aircraft operation tables, the transported passenger miles for GA operations in 2000 were estimated as 3 billion. The model estimates that 59% of current GA traffic is routed through control-towered airports (which account for only 14% of airports in the model). For the same airports selected in the model, statistics compiled from the NTAD database indicated 53% of GA traffic is routed through those airports (Table 3). A sample of the model output is given in Table 4.

### CONCLUSIONS AND RECOMMENDATIONS

The number of person trips in 2000 estimated using the general aviation airport choice model amounted to 6 million. This number agrees with the results from a top-down analysis performed by LMI using TAF and GAATA data. From this observation, the authors believe that the model is credible enough to be used as a means of estimating GA aircraft operations at national and regional levels.
Potential future studies to enhance the model capability follow.

- A discrete choice model should be developed to model GA operations because these types of models possess certain attributes over synthetic models. [Ortuzar presents a summary of some of these attributes (23)]

- Different formulations must be investigated for the pseudo-gravity model because the value of 0 obtained for \( \alpha \) in the current formulation suggests that access time is not critical in the travelers’ decision-making process.

- The current analysis could be conducted with the use of census tract data to improve model accuracy.

- Access and egress distances could be used in place of access and egress times because of the difficulty of obtaining drive times.

- Initially, the number of aircraft based and later itinerant operations at an airport were used as estimates of GA operations; in subsequent studies, other predictive variables should be incorporated into the model, and the use of drive times by using geographic information system–based tools should be investigated.

- The current output in the form of annual operations could be converted into daily trips and eventually hourly departure schedule. The resulting departure schedule could then be fed into air traffic network models such as TAAM, AOM/AEM (Virginia Tech), or

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**TABLE 3 Operations Through Towered and Nontowered Airports**

<table>
<thead>
<tr>
<th>Airport Type</th>
<th>% General Aviation Operations</th>
<th>Model Estimates</th>
<th>NTAD 2001</th>
<th>No. of Airports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Towered airports</td>
<td>59</td>
<td>53</td>
<td>474</td>
<td></td>
</tr>
<tr>
<td>Nontowered airports</td>
<td>41</td>
<td>47</td>
<td>2872</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>3346</td>
<td></td>
</tr>
</tbody>
</table>

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**TABLE 4 Model Estimates: Selected Airports**

<table>
<thead>
<tr>
<th>No.</th>
<th>Airport ID</th>
<th>Airport Name</th>
<th>State Name</th>
<th>Control Tower</th>
<th>Estimated Operations from Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Single Engine</td>
</tr>
<tr>
<td>1</td>
<td>15Z</td>
<td>McCarthy</td>
<td>AK</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>16A</td>
<td>Nunapitchuk</td>
<td>AK</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>4K0</td>
<td>Pedro Bay</td>
<td>AK</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>7KA</td>
<td>Tatitlek</td>
<td>AK</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>9A8</td>
<td>Ugashik–New</td>
<td>AK</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>A63</td>
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<td>AK</td>
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<td>0</td>
</tr>
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<td>ADK</td>
<td>Adak</td>
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<td>AK</td>
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<td>18</td>
</tr>
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<td>Kake</td>
<td>AK</td>
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(continued on next page)
LIMNET-SATS (developed by LMI) to assess the impact of GA operations on the NAS.

The output from the model may be used in additional analysis to derive macroscopic measures of effectiveness such as travel time benefits, noise impacts, fuel and energy usage, nonuser economic benefits, air transportation system congestion, and delays. These metrics are critical for decision support and policy making at regional and national levels.

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REFERENCES


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