Integrated Framework and Assessment of On-Demand Air Service in Multimodal Context

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On-demand air service presents a potentially viable alternative to road transport and commercial air transport in a regional transportation system. The objective of this research is a framework to better understand the performance and economic requirements for this mode. An integrated modeling framework is presented in this paper that models in composite fashion a regional transportation system including three principal modes of transport: road transport, commercial air transport, and a hypothetical on-demand air service mode, which can be configured differently for each simulation. Demand forecast modeling is based on the traditional four-step process, including a multinomial logit model for traveler mode choice and the network assignment carried out on a “composite network” consisting of all the modal networks. Scenarios with varying on-demand air service network sizes and price structures are presented as case studies to illuminate the most appropriate service networks for on-demand air service. Assuming typical very light jet aircraft parameters, the studies show that most of the demand for on-demand air service lies in medium-range trips (~200 miles). On-demand air service can also provide competitive service at its high cost for longer-range trips in spite of having superior capability, Finally, the framework demonstrates a viable analytical tool for studying transportation systems with multimodal interactions.

I. Introduction

Road transport in the United States is inexpensive and convenient for short-range trips. It is also aided by an extensive highway infrastructure. For this reason, it is the mode of preference for all intercity trips in the range of 100–300 miles. Commercial air transport, on the other hand, offers unparalleled benefits of speed and convenience (usually) for long-range trips (>500 miles). Additionally, a smaller but finite fraction of trips are made by alternative modes of transportation. However, for trips in the range of ~300–500 miles, none of the dominant modes offer an efficient solution. To effectively satisfy the needs of passengers in this range (~300 miles), the concept of on-demand air service (ODAS) has been proposed.

ODAS is a term that refers to transportation services that operate aircraft of 4–6 occupancy flying in and out of small public-use airports and provide on-demand or near-on-demand service to the passengers. Such operations are often called “air taxi” because they are envisioned to provide nonscheduled service as opposed to the scheduled airlines, though this term presents difficulty because some scheduling is involved in a typical ODAS business model. The small airports are distributed better geographically than the airports used by scheduled airlines; thus, the time taken to access the airport nearest a passenger’s origin and destination is less than that for a comparable commercial air trip. Additionally, the ground time associated with a trip by scheduled airline, such as security checks and baggage check-in, is reduced at small airports (and possibility of connection eliminated). For these reasons, ODAS is expected to provide quicker (but not necessarily cheaper) service than commercial air travel for origin–destination pairs that lie within the small aircraft’s range.

However, the implementation of this concept so far has seen only mixed success. There are dividing opinions on feasibility of integrating this new mode into the national transportation system. The issues raised include economic feasibility of operating the very light jet (VLJ) aircraft on an air-taxi basis [1], the potential demand for such a service [2,3], and integrating the ODAS operations into the National Airspace System (NAS) [4,5]. On the technology readiness level, VLJ aircraft have shown advancements in propulsion and avionics that result in significantly lower acquisition and maintenance costs compared to the next class of aircraft (light business jets) [5]. But the operational feasibility of the service depends on many other factors, such as the demand distribution, price structure, service network, etc. Such factors are not comprehensively studied in the literature.

From the perspective of a regional transportation policy maker, potential impacts of integrating a new mode such as ODAS into the existing transportation system are not clearly understood. This problem is confounded by the fact that, when an aspect of transportation, say environmental policy, is analyzed from a single-mode perspective, it often results in a myopic understanding of the overall system behavior. Some integrated frameworks are emerging, for example the multimodal approach in [6] that takes into account many other factors, such as the demand distribution, price structure, service network, etc. Such factors are not comprehensively studied in the literature.

The work presented in this paper seeks to further address this need for an integrated, flexible framework. Our purpose is twofold: 1) a method development effort to create an integrated framework to study a regional transportation system with its modal interactions and 2) insightful sensitivity studies examining utility provided by varying degrees of ODAS service introduced in the regional transportation system. Existing regional transportation system elements, including automobile transport and commercial air transport, are modeled using available data. A hypothetical ODAS mode, which is configurable, is then introduced in this transportation system. Socioeconomic data of the region are used to estimate the overall intercity transportation demand in the region. We leverage prior published work on an ODAS-focused stated preference survey. Finally, tools from demand forecasting process and discrete choice modeling are used to predict the demand for each mode of transportation. The focus here is on the demand for a transportation mode; therefore, factors related to the supply dynamics of the transportation mode (such as capacity constraints, price formulation,
etc.) are considered external and are based on reasonable assumptions.

II. Prior Research

Intercity travel demand forecast models study the socioeconomic factors of a region to determine the overall travel demand in the region and then compare different modes of transportation available for travel in the region to determine their relative demand. The main components of such a model are a macroscopic model of the transportation networks, a socioeconomic model of the demand, and an analytical or empirical model of how a traveler chooses a transportation mode for a given trip.

There have been a handful of efforts to estimate intercity travel demand across the entire U.S. since the 1970s. Ashiabor et al. [3] provide a broad overview of such national intercity travel demand models. Most of these models employ the same basic structure, although the analytical and simulation tools involved in each step of the process have evolved.

Most commonly, logit models are used for modeling the disaggregate travel mode choice behavior. Logit models were developed as a part of the discrete choice theory, which attempts to capture the human process of choosing from a set of discrete alternatives given the user’s perception of the utility of each alternative. Ashiabor et al. [3] provide an overview of the logit models developed for intercity travel. These models use socioeconomic data of a region from sources such as the U.S. Census to obtain the traveler attributes (such as household income, education level, etc.). Additionally, data about transportation modes are used to obtain the attributes of the mode (such as travel time and cost for a particular trip on the mode). The model then attempts to establish a correlation between the traveler attributes, the transportation mode attributes, and the traveler’s choice of the mode for a particular trip.

Naturally, the logit models need credible statistical data for calibration. Therefore, disaggregate travel surveys need to be conducted to gather data about individual traveler choices for their typical intercity trips. Historically, as the disaggregate travel surveys evolved, so did the logit models. All of the models used versions of National Travel Surveys conducted by the Bureau of the Census and the Bureau of Transportation Statistics (BTS).

Most of the existing demand models include a combination of road, transit, rail, and commercial air transport. However, only a few models have looked into the general aviation (GA) or the newly emerging ODAS segment. In a model called the Integrated Air Transportation System Evaluation Tool developed for NASA, Dollyhigh [2] develops a tool for predicting the total number of potential person trips that can be attracted by various GA operations, such as self-piloted single-piston engine aircraft, fractional ownership business jets, and air taxi. In another similar attempt, the model developed by Mane and Crossley [7] investigates the effect of different pricing strategies for air taxi and fractional ownership GA operations on the potential demand captured. Both of these models provide excellent references for comparing any demand analysis done with Small Aircraft Transportation Service. However, both models focus on demand prediction for GA operations and do not necessarily stress integrating these models into a larger regional transportation system.

There are two recent models that do include such analysis: the Transportation Systems Analysis Model (TSAM) model developed at Virginia Polytechnic Institute and State University [8] and the Mi simulation tool developed at Georgia Institute of Technology [9]. Both of these build a model of national transportation system including road, commercial air, and GA transport and attempt to predict the demand for each mode of transportation, while considering the multimodal interactions. In addition, the TSAM model is also tied to the more elaborate NAS simulations such as ACES to simulate average daily traffic patterns given the demand input.

The present work builds on the methods in the existing demand forecast models with two key additional capabilities. First, the network modeling uses a unique composite network, which encapsulates all of the modal networks. This addresses the multimodal interactions directly and explicitly in the modeling. Second, the ODAS mode is introduced as a hypothetical mode, with fully configurable parameters. Therefore, it is possible to perform case studies that compare different ODAS models in the context of a regional transportation setting.

III. Model Description

The objective of the framework is to form a composite macroscopic model consisting of commercial air, road transport, and the hypothetical ODAS modes. Stated preference surveys conducted to gauge the traveler response to ODAS suggest that this mode is competitive in ranges up to 650 miles [10]. For a nascent mode of transport such as ODAS, very little actual data are available concerning traveler preferences for this mode. In the absence of such data, the stated preference surveys attempt to capture the most important attributes of this mode from a traveler’s perspective. For longer ranges, the time savings offered by ODAS compared to commercial air travel are counterbalanced by high costs. Thus, the research studies a regional transportation system (in which maximum distance between any origin–destination pair is less than 650 miles) instead of the entire national transportation system. For convenience, the geographical extent of the regional transportation system studied includes the three Midwestern states of Illinois, Indiana, and Ohio. The region covers 282 counties spread across the three states.

A. Network Models

The road network is modeled by using geographic information system data about highway links, obtained from the National Transportation Atlas Database (NTAD) 2009 [11]. The highway links consist of interstate highways, U.S. highways, and state highways. An intersection of any two highway links is defined as a highway node. NTAD also includes the annual average daily traffic (AADT) data for highway links, which is useful for calculating driving times on them. The highway network thus modeled consists of 3145 nodes connected by 5070 links.

For ODAS operations, all public-use airports with runways greater than 3000 ft are deemed available. Locations of these airports are also extracted from NTAD. There are 357 such airports in the study region, which have a fairly uniform geographical distribution. Because every airport is connected by road, it is also a node on the road network.

The commercial air network (operated by scheduled airlines) is extracted using the Air Carrier Statistics data reported by the BTS. Form T100D (segment) of BTS consists of monthly data reported by air carriers about aircraft type, passenger capacity, ramp-to-ramp time, and enplanements on all of the origin–destination routes served by the carrier. All of the airports with at least one daily flight, and located within the geographical area of the study region, were included in the regional commercial air network to begin with.

However, because of the hub-and-spoke nature of the commercial air network, many itineraries are routinely routed through a major hub situated far from the direct origin–destination path. Therefore, simply selecting the airports situated in the geographical area of the study region does not truly represent the network available to passengers in this area. For example, Detroit is a major hub and may serve as a connection point for an itinerary involving origin in Illinois and destination in Ohio. But because Michigan is not a part of study region, Detroit is not included in the regional commercial air network. To overcome this shortcoming, the following potential hubs located near the study region were included in the regional network: Detroit, MI (DTW), Saint Louis, MO (STL), Louisville, KY (SDF), and Pittsburgh, PA (PIT). The choice of these external hubs was subjective, determined by observing the annual airport traffic at these airports and their proximity with the study region. Naturally, it is not possible to truly isolate a regional commercial air network from the entire national network. Note here that the commercial airports are also nodes on the highway network.

*Bureau of Transportation Statistics (BTS), Data available online at http://www.transtats.bts.gov/ [accessed May–June 2009].
Another issue for commercial air mode is how to determine the capture market of a commercial airport, the amount of demand that will originate from a certain commercial airport (excludes transfer passengers). Capture market computation is complicated by the possibility of travelers flying from an alternative airport (not closest) due to cost considerations. This study restricts the capture market of a commercial airport to the demand in the county where the airport is located. Figure 1 shows the network models.

The service network for ODAS forms a design variable for this study. During simulation case studies, a subset of the available public-use airports is chosen to represent the ODAS service network. The ODAS network is considered a complete network to represent the on-demand nature. In other words, in contrast to the commercial air network, there are no scheduled links in the ODAS network, and any origin–destination demand can be met with a direct link.

B. Demand Description

In keeping with the macroscopic nature of the framework, an annual overall intercity travel demand is sought. This demand is expressed in the form of an origin–destination matrix \( D \), where \( D_{ij} \) represents the total annual intercity person trips between \( i \) and \( j \). Because the present study focuses mainly on the mode choice process, the overall demand data from other similar previous studies can be used. Colleagues working with the TSAM model provided the overall demand forecast data for this study.

TSAM uses a county as the smallest geographical unit, and a year as the time unit. The only socioeconomic parameter used as the traveler attribute is the annual household income. The travelers are divided into five groups according to their annual household incomes: $30,000 or less; $30,000–$60,000; $60,000–$100,000; $100,000–150,000, and $150,000 or more (hereafter referred to as IC1 to IC5, respectively). Further, the trips are divided according to their purpose into business and nonbusiness trips. This leads to 10 different combinations of traveler trips (five income brackets and two trip types). Therefore, demand forecast is obtained in the form of 10 origin–destination matrices, each matrix of the size 282 × 282 (with the total number of counties in the study region being 282).

An important characteristic of the intercity trips forecast in TSAM is that all of the trips are at least 100 miles long. This is necessary to keep out the commuter trips. Forecasting commuter trips within metropolitan areas is a completely different task with its own separate methodologies. Therefore, the trips included in the data are only intercity trips that would not qualify as commuter trips. The demand numbers used in this study correspond to year 2002. The demand for future years can be estimated using demographic projection data such as Woods and Poole.\textsuperscript{††} Figure 2 shows the summary of demand.

A quick analysis of the overall demand gives the following insights. The total number of annual intercity trip equals approximately 50 million. The total population of the study region according to Census 2000\textsuperscript{††} is around 30 million, and the total number of households around 12 million. That corresponds to approximately four trips per household annually. As expected, the total number of personal trips exceeds the number of business trips across all income brackets. One of the major reasons for this is that personal trips often consist of an average trip party of more than one person, while business trips are often taken solo. Income brackets 2 and 3 include the most number of trips because a relatively large fraction of total population lies in these income brackets. Also, Fig. 2b shows that average trip distance is relatively short (143 miles), and most of the trips lie in this distance region. It can therefore be expected that road transport (being the most dominant mode of transportation for short-range trips) will have the biggest share of the demand and that, for any mode, the average trip distance will be influenced sharply by this overall demand distribution.

The basic geographical unit in the TSAM model is a county, as reflected in the size of the demand matrix. In comparison, the basic geographical unit in the present study will be a node on the highway network. Therefore, the demand matrix imported from TSAM needs to be modified accordingly. To distribute the demand inside a county, Census data about population centroids are used. Population centroids are areas of high population density in a county. All of the population centroids in the Census database with population > 5000 are chosen. Each population centroid is assigned to the highway node nearest to it. Then, the demand is simply distributed across the population centroids in a county according to the population distribution. Because the demand representation is distributed across several population centroids instead of a single point, the intermodal interactions such as effect of dense highway traffic on the airport accessibility can be better studied. The original demand matrix has 282 rows and columns. The expanded demand matrix now has 1015 rows and columns (with 1015 being the total number of population centroids in the study region).

C. Mode Choice Model

A multinomial logit model is developed to represent the mode choice behavior of travelers. In this particular study, a traveler has a choice of three modes: road transport, commercial air travel, or ODAS. To model this discrete choice problem, the simplest form of multinomial logit model is used. Under this model, the probability of choosing the road transport for a given origin–destination trip is given by

\[
\Pi_{\text{road}} = \frac{e^{U_{\text{road}}}}{e^{U_{\text{road}}} + e^{U_{\text{air}}} + e^{U_{\text{ODAS}}}} \quad (1)
\]

where \( U_{\text{mode}} \) is the utility value of the mode for a given traveler for the given origin–destination trip. Therefore, the first step in using Eq. (1)
is to define the utility of an alternative. Considerable prior research has been done to identify the attribute space for intercity travel mode choice behavior. This utility depends upon the attributes of the traveler as well as attributes of the mode. Koppelman [12] led the early efforts in modeling and identified key variables such as travel time, travel cost, and level of service for the alternative; income, education level, and region type for the individual; and the trip type (business, personal, or personal business). Many logit models formed in the past have used these key variables to calculate utility and have given satisfactory results when calibrated with statistical data [3].

Because the overall demand was imported from TSAM, the traveler-trip attributes were fixed at income level and trip type. Travel time and the monetary cost were chosen as the mode attributes. Therefore, the utility of the mode \( m \) for a trip from origin \( i \) to destination \( j \), and an individual of type \( p \) is given by

\[
U_{m,i,j}^p = \alpha_t^p \times t_{m,i,j} + \alpha_c^p \times c_{m,i,j}
\]

where \( t_{m,i,j} \) and \( c_{m,i,j} \) are the time and cost for traveling from \( i \) to \( j \) by mode \( m \), respectively. Therefore, they are the mode attributes. The traveler attributes are represented by the coefficients \( \alpha_t^p \) and \( \alpha_c^p \). Because the travelers are divided into five groups by household income and the trips are divided into two types (business and personal), there are 10 distinct types of traveler trips. Hence, \( p \) varies from 1 to 10, and there are 10 pairs of calibration parameters \((\alpha_t^p, \alpha_c^p)\). Before using Eq. (2), it is necessary to define the values for the 10 pairs of \((\alpha_t^p, \alpha_c^p)\) and to devise a methodology to calculate the values of \( t_{m,i,j} \) and \( c_{m,i,j} \). The trip time and cost for each mode were calculated using the methods explained next.

**D. Travel Time and Cost Estimation**

The travel time and cost for each mode in a given origin–destination trip are calculated for the best route involving that mode. To calculate these values on a route, a composite network is created. Because both ODAS and commercial airports are also nodes on the highway network, the composite network consists of the highway nodes and all of the links including highway, commercial, and ODAS links. When the best route between an origin and destination is calculated, it may consist of links of more than one mode, including the highway links from origin to the origin airport, air links between the origin airport and destination airport (also including the connecting airport, if applicable), and the highway links from the destination airport to the final destination. Such a composite network automatically includes the multimodal interactions. For example, if the origin airport is situated in a metropolitan area such as Chicago, the time taken to reach it from the origin by highway will be long, because of the heavy urban traffic. This time is included in the overall time for the commercial air route, therefore potentially decreasing its attractiveness. In the stated preference survey conducted by Peeta et al. [10], it was found that one of the biggest incentives for ODAS is the availability of airports near origin and destination points, reducing the access time. The composite network also captures this characteristic because a longer distance from the origin to the nearest airport means a longer composite route. Once the travel time and cost are calculated for a single link for each transportation mode, the composite route values are calculated by simply adding the time and cost for each link included in the route.

The travel time on a highway link is estimated as follows. The Transportation Research Board’s Highway Capacity Manual [13] is a widely used source of acceptable methodologies to calculate performance attributes of highway links. This publication describes empirical methods of estimating highway capacities and average travel times. For planning models such as the present work, simple empirical models exist that can predict these parameters fairly well as long as traffic on a highway is below a certain fraction of the highway capacity. Beyond this fraction, the traffic flow is interrupted, and more elaborate methods that use vehicle queuing and traffic signal modeling have to be used. We use uninterrupted traffic flow modeling to estimate the average travel times. It has been empirically determined that travel time has a nonlinear relationship with the traffic volume on a highway links. Various functions have been developed to determine the exact nature of this relationship. Davis and Xiong [14] present a review of these functions and compare their relative performances in different conditions. We use the Bureau of Public Records (BPR) function here for three reasons: it has been proven to give reasonable estimates for uninterrupted flow that are not close to the saturation conditions; it needs the least amount of data; and it has fixed parameters, and thus there is no need to recalibrate it for every different application.

The BPR function states that, for a highway link,

\[
T_{avg} = T_{ff} \left( 1 + a \left( \frac{V}{C} \right)^\beta \right)
\]

where \( T_{avg} \) is the average travel time on the link, \( T_{ff} \) is the free-flow travel time on the link, \( V \) is the average traffic volume on the link, \( C \) is the traffic volume capacity of the link, \( a \) is a model parameter with default value 0.15, and \( \beta \) is a model parameter with default value 4. \( T_{ff} \), the free-flow travel time, is calculated by dividing the link length by the free-flow travel speed \( v_{ff} \). This is the speed an average driver chooses on a given road when there are no immediate distractions in terms of traffic or traffic signals. The value of \( v_{ff} \), for the highway links of different functional class (as defined by the Department of Transportation), is assigned as per recommendations given in the HCM [13] (Chapters 10–13). Table 1 describes the link classes and the free-flow speeds. To be consistent with the HCM methodology, a lower limit of 35 mph and a higher limit of 75 mph were imposed upon \( v_{ff} \).

The quantitative data about each highway link are extracted from the Highway Performance Measurement System data available in the NTAD. It includes information regarding the length, functional class, number of lanes, and AADT. The basic traffic volume capacity, needed to calculate \( C \) in Eq. (3), is also assigned as per the HCM [13].

\[\text{Fig. 2 Overview of demand: a) demand by income groups and trip types, and b) distribution of demand by origin–destination distance.}\]
recommendations (Exhibit 21–3). Table 2 describes the traffic volume capacity for different highway link classes.

The values given in Table 2 are average capacities. It was decided to calculate travel time on road links during peak hour, to address the negative effect of peak traffic in airport accessibility. The peak hour capacity is obtained by multiplying the previous values by the peak hour factor (PHF). In accordance with HCM recommendations (Chapter 13), a value of 0.92 is used for PHF for urban links and 0.88 for rural links.

The value of \( V \) in Eq. (3) is calculated using the AADT data included in NTAD. While AADT is measured in passenger cars per day, \( V \) is measured in passenger cards per hour per lane. This conversion is done using a parameter called the K-factor, which is an empirical parameter defined in the HCM directly as the ratio of peak hour traffic to average daily traffic. Default values for K-factor are 0.093 for urban links and 0.095 for rural links as given in the HCM (Exhibit 8–9). Thus, the value of \( V \) for a link is obtained by multiplying AADT with K-factor.

With these parameters, average travel time on each highway link is calculated using Eq. (3). Average travel cost is calculated simply by multiplying the link length by BTS estimated average cost of owning and operating a personal vehicle in the United States. The value of 20 cents/mile was used in this study, according to the BTS recommendations.

Calculating the total travel time on a commercial air link is made up of three parts: the processing and wait time at the origin airport, the ramp-to-ramp aircraft travel time, and the exit time at the destination airport. Further, if a path involves two air links (signifying a connection), the wait time at the connecting airport (called the connection time) is added. The processing, connection, and exit time of an air trip together is termed the ground time for that trip.

Data about ramp-to-ramp travel time on airline segments are available in the Bureau of Transportation Statistic’s (form 41 traffic) T-100 (segment) data set. It is the monthly data reported by certificated U.S. air carriers on passengers, freight, and mail transported. From this data set, data about total annual passenger volume and average ramp-to-ramp travel time were extracted for every link of the commercial air network in the study region. The process of calculating travel time between all pairs of (Midwest) airports in this network is as follows.

1) For each pair, compute all of the possible air routes in the network that involve at most one connection (meaning routes consisting of either a direct link or a connection at a hub airport). Routes involving two or more connections are discarded for obvious reasons in a regional transportation context.

2) For each route thus computed, calculate the total travel time, including process time at the origin airport, ramp-to-ramp time, connection time (if applicable), and the exit time at the destination airport.

3) Compute the average travel time between the origin and destination, weighted by the passenger volume on each route.

This average time is then used as the travel time for the origin–destination airport pair. Here, it must be noted that, by using the average time, we are destroying the possibility of presenting the traveler a choice of multiple air routes. Ideally, this distinction between air routes needs to be retained because it reflects the real-life scenario. For example, business travelers would choose direct routes, even if they were more expensive. By flying direct routes, they can save considerable travel time. In this study, it is assumed that a business traveler earning about $100,000/year assigns a value of travel time between $30 and $46 per hour [15]. On the other hand, personal trips and trips for travelers in lower income brackets may choose indirect routes; they likely take longer, but cost less. However, because of the decision to use simple multinomial logit model instead of a nested logit model, this extra dimension of the problem was left unexplored. At the regional level, the effect of this decision is not as pronounced as at the national level, where there is a much wider variety of air routes and fare combinations to choose.

Data about average processing and connection times for airports are not readily available. Therefore, some reasonable assumptions have to be made. BTS definitions about airport hubs were used for this purpose. According to these definitions, any airport that handles at least 1% of the national air passenger volume is classified as a large hub; airports handling between 0.25 and 1% are classified as medium hubs; and other airports are classified as small hub or nonhubs. Based on aggregate trends, the values in Table 3 were used.

These values are less than the national averages used in transportation models such as TSAM [4]. However, because these values are essentially based on some assumptions, it is important to study their impact on the model. For this reason, one of the simulation experiments involves a sensitivity study for changes in these values. It must also be noted here that the previous values, which together make the ground time of an air trip, make up a significant part of the total trip time. A quick analysis of the segment ramp-to-ramp times reported in T100 data and the previous values shows that, on average, about 30% of the total trip time consists of the ground time. This fraction decreases as the trip distance increases. This significant ground time is one of the major disadvantages of commercial air transportation for short distances.

For calculating the average ticket price for a given airport pair, the BTS Airline Origin and Destination survey, called the DB1B survey, was used. It is a 10% sample of airline tickets from reporting carriers. Data include origin, destination, and other itinerary details of passengers transported. Unlike the T100 data DB1B is not an aggregate data reported by the airline. It is a sample of individual traveler itineraries. As such, these data includes a lot of unwanted and unnecessary elements. The following filters were used while using this data.

1) Some of the itineraries were found to report unusually small fares. Assuming that these fares represent promotion fares, frequent-flyer rewards, or other such unusual instances, they were removed. Any fare less than $50 was removed in this process.

2) Some of the itineraries had unusually large travel party sizes. In many cases, it was found that the fares in such cases did not show normal trends. Such instances were removed.

3) Some of the itineraries were found to report unusually large fares. This typically occurred when the aircraft seating capacity

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Table 1 Free-flow speed on highway links by functional class (miles per hour)

<table>
<thead>
<tr>
<th>Functional Class</th>
<th>Urban</th>
<th>Rural</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interstate</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>Principal arterial</td>
<td>55</td>
<td>60</td>
</tr>
<tr>
<td>Minor arterial</td>
<td>55</td>
<td>60</td>
</tr>
<tr>
<td>Freeway/expressway</td>
<td>70</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 2 Highway link capacity (passenger cars per hour per lane)

<table>
<thead>
<tr>
<th>Functional Class</th>
<th>Urban</th>
<th>Rural</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interstate</td>
<td>2400</td>
<td>2400</td>
</tr>
<tr>
<td>Principal arterial</td>
<td>2100</td>
<td>1900</td>
</tr>
<tr>
<td>Minor arterial</td>
<td>2100</td>
<td>1600</td>
</tr>
<tr>
<td>Freeway/expressway</td>
<td>2400</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 3 Assumed airport processing, connection time, and exit time (minutes)

<table>
<thead>
<tr>
<th>Airport Type</th>
<th>Processing Time</th>
<th>Connection Time</th>
<th>Exit Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large Hub</td>
<td>45</td>
<td>30</td>
<td>20</td>
</tr>
<tr>
<td>Medium Hub</td>
<td>30</td>
<td>45</td>
<td>15</td>
</tr>
<tr>
<td>Nonhub</td>
<td>20</td>
<td>N/A</td>
<td>15</td>
</tr>
</tbody>
</table>
was low. These were probably instances of charted flights, aircraft rentals, or other such unusual cases. Such itineraries were removed. It is possible with further statistical analysis to separate average economy fare and average business fare. However, because the travel times for all of the air routes were averaged, it was decided to average the fares as well. Because travel fare essentially provides a tradeoff to the travel time, in the absence of multiple options for travel time, options for fare were deemed unnecessary.

Both the service network and aircraft performance for the ODAS mode form design variables in the present study. Therefore, no available data sets are used to define any parameters for this mode. The typical operating conditions and the potential impacts of using VLJ in an ODAS mode have been studied in [4,5]. The values for design variables during the experiments were used based on the trends highlighted in these sources. The design variables are explained next.

The first design variable is the price per passenger mile (ppm) for the service. The ticket price for an ODAS seat between a pair of airports is simply the great circle distance between them multiplied by ppm. The value of ppm for an ODAS operator depends upon various factors, including the type of aircraft, its acquisition cost, operating cost, typical load factor (number of passengers) for a trip, personnel cost, etc. Dollyhigh [2] includes life-cycle cost analysis for Eclipse 500, and assuming four passengers for a typical trip, calculates the ppm to be $1.72. This value is obviously sensitive to the load factor used. In their air taxi feasibility study, Mane and Crossley [7] estimate the direct operating cost of the Eclipse 500 to be $937 per hour. Assuming two passengers per trip, and using the nominal performance characteristics of Eclipse 500, this translates to a ppm of approximately $2.25. A detailed life-cycle cost analysis for a typical VLJ, including expected operational factors for a typical ODAS operator (such as 10–20% repositioning or empty flights) performed for the TSAM model, estimates that the ppm for a typical ODAS service will range from $1.85 to $2.25 [4].

The aircraft performance is represented by maximum cruise velocity \( v_{\text{cruise}} \) and maximum rate of climb \( v_{\text{c}} \), which make up the other design variables. More detailed aircraft dynamics are avoided for the sake of simplicity. For any given origin–destination airport pair, the flight profile of the aircraft is assumed to be simple climb–cruise–descent. The cruise altitude \( h_{\text{cruise}} \) is in general a function of the distance between the airports. Using these parameters, it is possible to calculate the ramp-to-ramp travel time for a give pair of airports using ODAS as simply the sum of time taken for the climb, cruise, and descent segments.

This concludes the description of travel time and cost estimation for a link on each travel mode. This can be used to estimate the time and cost for the best route involving each mode (which potentially involves more than one type of link). These values are then used to calculate the utility of a particular mode using Eq. (2).

### IV. Model Calibration and Validation

#### A. Calibration

After calculating the travel time and cost, the second part of Eq. (2) involves defining the values of the coefficients \( \alpha_i \) for each traveler trip type. These coefficients essentially capture the traveler attributes. Defining the values of the coefficients is the same as calibrating the utility model with existing disaggregate travel choice surveys. The 1995 American Travel Survey (ATS) is used for this purpose. It is one of the most comprehensive surveys conducted in the United States for the purpose of analyzing the long-distance travel preferences of Americans. The data in the ATS were collected by randomly choosing households across the entire United States to fill out a form requesting details about long-distance trips (>100 miles) each person in the household has taken in the previous year. The factors collected include, among other things, the household income, number, age and gender of the persons in the household, trip origin and destination, and the mode chosen for the trip. Note that, for calibration purposes, the ODAS mode was left out of the model, thus making the composite network consisting of only the road network and the commercial air network.

There are over 554,000 individual records in the survey. For each record, the information about origin–destination in ATS includes the origin state, the destination state, the origin and destination metropolitan statistical area (MSA), and the distance between origin and destination. The U.S. Office of Management and Budget defines MSA as one or more adjacent counties or county equivalents that have at least one urban core area of at least 50,000 population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties.

To calculate the travel time and cost using the model, the origin and destination have to be mapped onto the network nodes. This is done as follows. First, the ATS records are filtered to only include the trips within the study region. It is also filtered to include only the records pertaining to mode of choice as either road or commercial air transportation. This reduces the total data size to 18,500 records. If either the origin or destination happens to be in an MSA, it is identified by the name of the MSA in the ATS. However, an MSA typically has many counties included. Thus, all of the highway nodes lying in these counties form the origin (or destination) set for this particular record. If, on the other hand, either origin or destination is identified simply as non-MSA, then all of the highway nodes lying in the non-MSA counties in the corresponding state form the origin (or destination) set.

This way, a set of nodes for origin and destination is obtained. Then, the distance information in the ATS record is used to select the ordered pair of nodes from these two sets. The pair of nodes (one each from origin and destination set) with the distance closest to that mentioned in the ATS record is chosen. This way, the origin and destination are now mapped on the highway network. More than 95% of the mappings thus obtained result in the difference of less than 30 miles in the origin–destination distance in ATS and the distance on network.

After trying multiple utility models for the calibration purpose, the following model was selected. For a given origin–destination pair, the utility of mode \( p \) (either road transport or commercial air transport) is given by

\[
U_p = \alpha_1 t_p + (\alpha_2 + \alpha_4 + \alpha_5) c_p + \alpha_3 c_p^2
\]  

(4)

where \( \alpha_i \) is the time coefficient, \( t_p \) is the travel time for mode \( p \), \( c_p \) is the travel cost for mode \( p \), and \( \alpha' \) is the cost coefficient for the traveler from income group \( i \in \{1, 2, \ldots, 5\} \). The time coefficient \( \alpha_i \) is assumed to be the same for all income groups for the reason explained in Sec. III.D. For a traveler of income group \( i \), all of the cost coefficients except \( i \) are set to zero. Thus, these coefficients effectively act as dummy variables for any given record. This procedure is carried out separately for business trips and personal trips. The result of this calibration process is shown in Table 4.

The calibration results, while satisfactory, do not provide a uniformly good fit, as evidenced by the relatively low value/standard error (especially for higher income groups). This was also confirmed by an R-squared value of <0.5 for both business and personal trips. The quality of the fit especially deteriorates for the high-income

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Standard error</th>
<th>Value/standard error</th>
<th>( P(\mid Z &gt; Z) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business trips</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \alpha_1 )</td>
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<td>( \alpha_3 )</td>
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<tr>
<td>( \alpha_4 )</td>
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<td>0.00113</td>
<td>-4.98230</td>
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</tr>
<tr>
<td>( \alpha_5 )</td>
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<tr>
<td>Personal trips</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
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<tr>
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<td>0.0006</td>
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groups, due primarily to the fact that the ATS data volume is insufficient for high-income group. Hence, a more focused travel survey, with more data on regional trips taken by high-income groups, will be helpful in calibrating the model better. Another reason for a relatively poor fit is the relatively low fidelity of the commercial air network. The inclusion of choice for routes and fares will result in time and cost estimations for the air network that are better representations of reality.

In addition, the current algorithm will, in some cases, favor road transport mode. Whenever the travel time for road transport of a particular county–county pair is less than that for the air mode, most travelers will choose the automobile mode because road transport mode has a considerably lower travel cost (in terms of dollars per mile) than air mode. The lack of certain factors in commercial air network, such as flight frequency, departure times during the day, etc., becomes more deterrent to the choice of this mode, especially in short-range trips, where the door-to-door trip time for road transport and commercial air transport are comparable.

**B. Verification**

The model thus calibrated is run in the absence of a hypothetical ODAS mode. The only available modes are road and commercial air. Once the model is run, aggregate network data are analyzed for relative trip volumes on both modes. These data are then compared to ATS to verify the results. Figure 3 shows the results. All of the records were divided according to the trip distance into brackets of 50 miles. The fraction of trips that chose the commercial air for each bracket was calculated. The x axis in the figure corresponds to a distance bracket, and the y axis corresponds to the market fraction of commercial air for that distance. As the figure shows, the market fraction increases as the distance increases, and in the range of ~600 miles, over half of total trips are taken by commercial air. The matching of overall trend with the ATS data suggests verifies the implementation of the entire framework, containing the network models, mode attributes, traveler attributes and the mode choice logic.

The model also computes the traffic volume on all of the links on modal networks. Using these data, total annual number of enplanements at the commercial airports was calculated. These numbers were compared to the annual enplanements as reported in T-100*** (market) database for the year 2002. The T-100 market data describe the total number of person trips taken between an origin–destination airport pair. These data are filtered to include only the air links present in the market network. Figure 4 shows the results.

On the whole, the model underpredicts the total number of enplanements by about 16% (5.5 million computed by model as against 6.5 million reported in T-100). Also, the model overpredicts the number of enplanements for smaller airports and generally underpredicts them for the larger airports. This can be attributed to the relatively low level of fidelity of the commercial air network model. As described before, many details about the commercial air network are dropped for the sake of simplicity. For example, there is no information about flight frequency for a given route in the model, thus making even routes with less frequency appear as attractive as routes with higher frequency, as long as the travel time and price are similar. In addition, the overprediction may be due to the assumption that flights at small airports are fully reliable and the price of car rental at these airports is comparable with the rates offered in other places.

These two validation results prove that the model choice model and network assignment process exhibit correct trends. The validation results also help in understanding where the models fail to capture the real dynamics properly and predict where the accuracy of the model will be limited (and possible reasons for limitation).

**V. Simulation Experiments**

The purpose of simulation experiments is to observe the demand for each transportation mode as the nature of ODAS mode is changed. Three different simulation experiments are reported here. In experiment 1, it is assumed that ODAS can be provided between a pair of any two VLJ-ready airports in the study region. All 357 public-use VLJ-ready airports in the study region are considered as service airports. Essentially, it is assumed that ODAS with infinite capacity (in terms of fleet size and flight frequency) can be provided, to uncover the maximum demand possible for this mode. A baseline ppm of $2.25 is assumed. It can be expected that the demand volume and distribution are very sensitive to this value. Therefore, experiment 2 studies price sensitivity of demand on this same (infinite

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**Fig. 3 Model verification with ATS: commercial air market fraction by distance.**

**Fig. 4 Model validation with T100: annual enplanements at commercial airports for 2002.**
Air Service Demand

B. Experiment 2: Price Sensitivity of On-Demand Air Service

For on-demand air service, restricting the ground time to a small value is equally important as minimizing the airtime with better aircraft. Therefore, experiment 3 conducts sensitivity studies for the ground times of commercial air and ODAS networks.

To calculate the travel time and cost for ODAS, the performance parameters of the Eclipse 500 jet were used: cruise speed 425 mph, rate of climb 3314 ft/min, and cruise altitude 24,000 ft. In addition, a wait time of 15 min at the origin airport and an exit time of 15 min at the destination airport were added to the ODAS travel time (making the total ground time 30 min for any ODAS trip). Another simplification is that ODAS price was assumed to be ppm times the great circle distance between origin and destination airports.

A. Experiment 1: Maximum Possible Regional Demand for On-Demand Air Service

The first experiment consists of a hypothetical ODAS with infinite capacity, and every VLJ-ready airport is treated as an ODAS service airport. Figure 5 shows the market shares for the transportation modes by distance in this case. The tip of each bar in the figure is the combined share of commercial air and ODAS, and the rest is the market share for automobile. As the figure shows, most of the demand for ODAS lies in short distance brackets. The total market share is 9.26%. Commercial air dominates for trips longer than 400 miles and automobile transport dominates for shorter trips. This translates to approximately 2.5 million enplanements annually for ODAS in the study region (note that the ubiquitous availability of ODAS represents the limiting value in case of infinite capacity). The demand is very small for trip ranges of over 250 miles. It is worth noting that the typical VLJ has the capability to fly much longer ranges (e.g., the Eclipse 500 has a maximum range of 1300 miles). This is an indication of price, not the aircraft performance, being the limiting factor on the ODAS demand. The point-to-point nature of the service provides significant advantage in terms of volume for short-range trips.

Figure 6 shows the market fractions of ODAS and commercial air for different ODAS prices.

The demand for ODAS increases rapidly as ppm drops below $2. Also, the commercial air market fraction does not change for ODAS ppm above $2, indicating that, above this price, the ODAS cost for typical long-range trips is prohibitive; therefore, commercial air travel retains a significant fraction of these trips. Below $2, the commercial air market fraction decreases as ODAS prices drop. As Fig. 7 shows, for $1.5 per passenger mile, a significant fraction of long-range trips are captured by ODAS, but as price increases, the average trip distance for ODAS begins to drop rapidly. At $2.5 per passenger mile, most of the trips are shorter than 200 miles.

The overall demand analysis presented earlier indicated that much of the overall demand lies in short-range trips. Therefore, although a low ODAS price can effectively capture a significant portion of the long-range trips, the intrinsic nature of the regional transportation demand is such that there will always be a far greater demand (in terms of volume) for short-range trips.

C. Experiment 3: Sensitivity Analysis for Commercial Air Ground Times

Earlier experiments bring out two important factors that influence the demand distribution for ODAS.

1) ODAS price is the main limiting factor against a greater fraction of person trips switching from existing modes to ODAS. The time savings offered by ODAS should be significant to justify its high cost.

2) Especially for commercial air travel, a significant part of the total travel time comprises the ground time: time spent in the airports for check-in, security, etc.

The ground times used for the commercial air travel, as mentioned in Table 3, do not have a well-established basis. They are based on some reasonable assumptions and looking at trends in existing literature. These values, however, are on the optimistic side (from the perspective of commercial air traveler). In reality, the ground times can be significantly higher than this. In such cases, the total travel time for commercial air transport increases. One of the key factors in favor of ODAS is that it can use the smaller airports, cutting down

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**Figure 5** Market shares by distance for experiment 1.

**Figure 6** Demand sensitivity to ODAS price.

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capacity) ODAS network. Similar sensitivity studies are also carried out on the ground time for the commercial air and ODAS networks. The importance of carrying out these studies is highlighted by the fact that a significant fraction of the total travel time on a commercial air flight consists of the ground time. Therefore, for a competitive ODAS service, restricting the ground time to a small value is equally important as minimizing the airtime with better aircraft. Therefore, experiment 3 conducts sensitivity studies for the ground times of commercial air and ODAS networks.

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significantly on process times at these airports. It is therefore important to study if any increases in ground times for the commercial air travel result in additional demand for ODAS.

The values for ground times used in experiment 1 are taken as the nominal values. In experiment 3, the ground times are changed from their nominal values, and effects on overall demand distribution are analyzed. In the experiment, the ground time for each air trip is changed from its nominal value by a common factor $f$. Therefore, $f < 1$ would mean a decrease in the ground time from nominal case, and $f > 1$ would mean an increase in the ground time from nominal case. The value of $f$ is changed from 0.5 to 2, in increments of 0.1, and the results are plotted as sensitivity analysis. Thus, $f = 0.5$ represents the most optimistic scenario for commercial air transportation, where all of the ground times are cut in half (across the entire commercial air network), and $f = 2$ represents the worst-case scenario where the ground times are doubled across the entire network.

To study the sensitivity of the demand to the ODAS ground times, the same analysis is carried out with the ODAS ground time changed from its nominal value of 30 min. It is multiplied by $f$, where $f$ is changed from 0.5 to 2 in increments.

Figure 8 shows the overall market shares of commercial air travel and ODAS as $f$ is changed. In Fig. 8a, the commercial air market fraction drops as $f$ is increased (from 16% to 5%). But the corresponding increase in ODAS market share is not very pronounced (from 4.3% to 4.5%). This implies that, as average trip time for commercial air travel increases, demand shifts away from it, but ODAS does not capture a significant part of this demand. A similar trend is observed in Fig. 8b. The ODAS market fraction drops as $f$ is increased (from 7% to 2%). But the corresponding increase in commercial air market share is not very pronounced (from 11.4% to 11.6%). In short, in both cases, as either ODAS or commercial airlines lose the market share because of increased ground times, the demand shifts predominantly to ground transport. This can be explained as follows. If the ground times for long trips (for which the commercial air transport is the predominant option) become unacceptable, it still does not make the prohibitively high costs of ODAS for such long trips an attractive option. On the other hand, if the ODAS ground time becomes unacceptably high, it loses its time advantage over ground transportation for short trips, which make the significant part of ODAS demand. This emphasizes the narrow margin of trip distances where ODAS can realistically stay competitive to the existing modes of transportation.

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These experiments prove one thing beyond doubt. Given current estimations of how much it would cost to own and operate a VLJ aircraft, the ODAS price is such that only short-range trips are affordable. These trips would normally be covered by automobile in the absence of ODAS. The commercial air transport dominates the market in long-range trips and would continue to do so as long as it is not possible to drastically reduce the ODAS costs.

VI. Conclusions

This paper described an integrated modeling framework for analysis of a multimodal regional passenger transportation system. The model integrates auto transport, commercial air transport, and hypothetical ODAS modes into a composite network. The main objective of the framework is to support regional transportation system planning that is informed about potential modal synergies and thus guide smart investment. Capturing multimodal interactions was therefore one of the important criteria in evaluating such a framework. This objective was achieved by implementing the concept of composite network.

The framework was used to study the possible demand distribution for a hypothetical ODAS transportation mode, given a price structure that has been deemed feasible by studies on VLJ aircraft. The simulation experiments offer an insight that is consistent with prior research in this area. It is noted that, for the given price structure, most of the demand for ODAS comes from medium-range trips (100–300 miles) that were using automobile transport in the absence of ODAS. For these ranges, ODAS offers significant time saving over automobile transport irrespective of aircraft characteristics; therefore, price is the important factor. Also, ODAS does not capture a
significant portion of long-range trips from commercial air transportation, owing to high costs. The studies also highlight the importance of choosing the right price structure and other service characteristics such as ground time for an ODAS operator.

From a methodological perspective, the work describes a viable analytical model for studying transportation systems in an integrated manner. The use of composite network enables capturing multimodal interactions more effectively than the existing methods. This is especially important given the increasing emphasis on seeking integrated analyses and solutions in transportation systems engineering. Some of the present assumptions used in this work may limit the immediate applicability of the model for investment planning decisions; however, this provides opportunity for improvements and, more importantly, interaction with related academic models concerning new survey-based data sources.

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