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Commuter demand estimation and feasibility assessment for Urban Air Mobility in Northern California

Mihir Rimjha [*], Susan Hotle, Antonio Trani, Nicolas Hinze

Virginia Polytechnic Institute and State University, School of Civil and Environmental Engineering, 750 Drillfield Drive, Blacksburg, VA 24061-0002, United States

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ABSTRACT

This study aims to estimate passenger demand for Urban Air Mobility (UAM) and analyze the feasibility of operating the system in Northern California. UAM is a concept mode of transportation that is designed to bypass ground congestion for time-sensitive, price-inelastic travelers using autonomous, electric aircraft with Vertical Takeoff and Landing (VTOL) capabilities. This study focuses specifically on commuting trips, which are frequent and considered relatively more time-sensitive than other types of personal trips. The UAM mode's feasibility is studied using sensitivity analysis of UAM demand to cost per passenger mile and the number of vertiports placed in the region. This study also explores the spatial distribution of UAM demand in Northern California, which further helps in identifying the major commuter trip-attraction and trip-production zones for the UAM mode in the region. The results indicate that sufficient UAM demand for commuting trips can only be reached at optimistically low UAM offered fares. These fare levels could be challenging to obtain given the high real estate cost in Northern California's urban regions. Moreover, the reliability of the UAM mode must be comparable to the automobile mode; otherwise, it loses significant demand with increasing delays. The results also show that the commuting flows with promising UAM demand in Northern California are heavily one-directional, with San Francisco Financial District being a major attraction. Other types of trips should also be considered along with commuting trips to generate an economically viable system and reduce deadheading.

1. Introduction

On-Demand Mobility (ODM) could change how people travel in the future. With ODM, "vehicle routes and schedules are not fixed a priori; instead, they adapt dynamically to serve incoming transport requests" (Čertický et al., 2015). Today's society has seen implementations of ODM through mobile app-based taxi-hailing services, including Lyft and Uber. However, in the future, technologies such as autonomous vehicles and 2- or 4-person electric aircraft with vertical takeoff and landing (VTOL) capabilities are expected to be fully in service to the general public (Munster, 2017; Davies, 2016). ODM's impact will be two-fold by adding modes to a traveler's choice set and increasing the operational efficiency of existing transportation systems during peak-hour commutes.

The VTOL concept, also known as Urban Air Mobility (UAM), has gained considerable attention in recent years for its anticipated appeal to time-sensitive, price-inelastic travelers. It would provide a fast mode of transportation to bypass the congestion of ground

* Corresponding author.
E-mail addresses: rimjha@vt.edu (M. Rimjha), shotle3@vt.edu (S. Hotle), vuela@vt.edu (A. Trani), nhinze@vt.edu (N. Hinze).

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transportation systems. America's most congested cities have the opportunity to receive the most significant benefit from UAM by reducing the delays and overall travel times. For example, in 2015, "the average San Francisco resident spent 230 h commuting between work and home – that is half a million hours of productivity lost every single day" (Uber, 2016).

The UAM network will consist of vertiports, which, similar to helicopter pads, can be located in fields or on building rooftops. To use the UAM mode, commuters will first need to travel to the nearest vertiport to board a UAM aircraft. For this research, vertiport accessibility modes include walking or an ODM ground vehicle such as Uber or Lyft. We assume no public parking available at the vertiports. The commuter will then board a UAM aircraft to fly to the vertiport nearest to their destination, similarly relying on walking or ODM for the last-mile transportation. To date, a few companies have offered a similar service to UAM by using helicopters between helipads, such as BLADE with shuttle rides in the Bay area, Los Angeles, and New York (BLADE., 2019). However, these services are limited to very few Origin-Destination (OD) pairs. Helicopter commuter services are expensive compared to the UAM price estimated by Booz-Allen-Hamilton in a study supported by NASA (Hamilton, 2018) and an autonomous aerial vehicle manufacturer, E-hang (EHang, 2020). The former estimated $6.25 per passenger mile in the near-term which could drop by 60% ($2.50) in the long-term, whereas the latter ran a conservative financial model with the unit fare of $4 per passenger mile for the near-term, which could drop significantly considering economies of scale and efficiency gains.

In addition to vertiports, the UAM concept utilizes electric vehicles with advanced avionics and VTOL capabilities. UAM aircraft may be fully autonomous in the long-term, but they would include a safety pilot in the initial stages of deployment. The aircraft is expected to be a viable mode alternative for commuting. UAM aircraft will have a maximum range between 120 and 183 miles (Uber, 2016; Hawkins, 2017) with a top cruise speed between 150 and 200 mph (Uber, 2016). While this mode will be costly initially, similar to a helicopter, it could become more affordable over time, making it more feasible to use on a frequent basis (Whittle, 2017). Uber has already invested in VTOL by planning an initial offering of its UberElevate product in three test cities (Uber, 2018) by the year 2020.

This study aims to analyze the feasibility of offering UAM services to the commuter market in the Northern California region, centered on San Francisco. This study involves developing a model to estimate UAM commuter demand for different scenarios with varying vertiports in the region and cost per mile (CPM) to the traveler. The UAM demand model utilizes a calibrated mode-choice conditional logit model based on the add-on National Household Travel Survey (NHTS) data. The demand model is used to obtain a network of UAM vertiports placed optimally to maximize the UAM demand iteratively. The analysis considers the household income distribution in the region and the number of vertiports and CPM.

2. Literature review

Existing literature contains several studies that assess the future of UAM. Booz Allen Hamilton performed a comprehensive market study of UAM for the National Aeronautics and Space Administration (NASA) (Hamilton, 2018). They focused on ten major urban areas in the United States and witnessed high variability in UAM demand across the cities. A logit model was calibrated using two variables, travel time and travel cost per median hourly household income, using the American Community Survey (ACS) 2016 data and a general population survey that the company conducted. Their Monte Carlo simulations estimated a demand of close to 80,000 daily passengers across the United States served by 4000 UAM vehicles for all trip purposes. This study assumed that UAM would use existing infrastructure for vertiports, specifically already built helipads and airports. However, the locations of helipads and airports are not optimized to maximize demand. Using existing facilities could significantly disadvantage the UAM mode as intermodal distances could increase. The analysis was also performed at the census tract level, limiting the ability to estimate the mode choice of individuals and mode-specific trip characteristics.

Fu et al. (Fu et al., 2019) performed a mode-choice analysis in the UAM environment based in Munich, Germany. The study included data collection from an online stated-preference survey and the creation of several discrete choice models. The study found that for commuting, public transit is the most desirable choice, followed by auto, whereas UAM selection is the least likely. Their model estimates suggest a relative increase of acceptance for autonomous modes in the higher-Value-Of Time (VOT) group. Since this study is based on a stated-preference survey, it is possible that results could differ from actual, revealed-preference behavior.

Bulusu et al. (Bulusu et al., 2021) developed a traffic analysis method to estimate the maximum number of people that can benefit from UAM in a metro area. As a sample application, they applied their methodology to 32757 commute trips in San Francisco Bay Area. Their study estimated multi-modal UAM trip itineraries and compared travel time savings by UAM compared to the car for different cases of vertiport transfer times. Commuters who only shift mode with 50% or more of travel time savings are considered to have a high value of time. They found that during high congestion and even with a long transfer time of 15 min, 45% of commuters with the high value of time could benefit from UAM on a travel time basis. This indicates high UAM demand potential in the region. However, the study did not consider commuters' willingness-to-pay, which is essential to estimate total UAM passenger demand.

Balac et al. (Balac et al., 2019) explored the prospects of the UAM service in Zurich, Switzerland. They created experiments with combinations of various UAM passenger processing times, cruising speeds, and variable costs, assuming a base fare of 6 Swiss Francs (CHF). Their experiments found that when the variable costs exceed 1.8CHF/km, the UAM service failed to attract high passenger demand and, therefore, making the service only attractive to the very high-income market segment of the population. The study concluded that the UAM market share in small urban areas like Zurich is low, but for metro areas with dense populations, the UAM market share in the transportation system could be significant. Limitations of this study include that the experiments were carried out on only a 10% population sample with a pre-defined network of nine-vertiports based on local expertise. Pre-defined vertiport locations might not maximize the UAM demand and, therefore, decrease the mode's demand potential. Building upon this study, Balac et al. (Balac et al., 2019) estimated demand for the aerial vehicle in the Zurich region using multi-agent-based simulation paired with a mode-choice model. Using Uber Black price for the aerial vehicle, the demand was found to be low, and the aerial vehicle would mostly

Fig. 1. Northern California 17-county study area.

serve mid-distance trips requiring high detour factors due to terrain. This study focused on the Zurich region, and its findings may not apply to an urban region in the USA due to differences in commuting patterns, terrain, congestion, demographics, public transit network, mode choice availability, etc. Nevertheless, the study provides significant reference and validation points.

Similar efforts are being put to explore the human factors involved in the integration of UAM into the current transportation system. Analyzing the user's perception and degree of public acceptance is equally important in the development of UAM. Al Haddad et al. (Al Haddad et al., 2020) explored various factors affecting the adoption and use of UAM using a stated preference survey. After modeling adoption time using exploratory factor analyses and discrete choice models, they found safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics as important factors in the adoption of UAM. Eker et al. (Eker et al., 2019) studied individuals' perceptions of benefits and concerns from UAM utilization, potentially affecting its adoption by the commuting population. They statistically analyzed data (collected through online-survey) using grouped random parameters bivariate Probit models. They found that an individual's perception towards the use of UAM is affected by various socio-demographic, behavioral, and attitudinal attributes. Behme and Planing (Behme and Planing, 2020) performed a qualitative analysis to study customer acceptance of UAM using individual interviews. They found that UAM acceptance would increase if the system is made more relevant and better known to the public. Furthermore, the study emphasized coherent intermodal connections for better acceptance of UAM in the current transportation system.

While the authors of this paper are aware of the factors affecting the adoption of UAM in the current transportation system, the study assumes full adoption of UAM and focuses on the feasibility of operating UAM from an economic perspective. The study presented in this paper builds upon previous work completed by Syed et al. (Syed et al., 2017), where a conditional logit model is calibrated to estimate UAM demand in the Northern California region. This study builds on Syed et al. (Syed et al., 2017) by creating a

Table 1
Datasets used in the analysis.

Datasets	Data Resolution	Task
National Household Travel Survey-2017 Add-on Data ("Transportation Secure Data Center.", 2019)	Location Coordinates	Mode Choice Model Calibration
Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) (Census Bureau, 2015)	Block-group	Parking Cost Estimation Model Application
American Community Survey-2017 (U.S. Census Bureau; American Community Survey, 2017)	Block-group	Mode Choice Model Calibration Model Application

new robust mixed conditional logit mode-choice model that captures the unobserved heterogeneity, which follows the method described in Greene et al. (Greene and Hensher, 2007). Eker et al. (Eker et al., 2020) discuss in detail the unobserved heterogeneity present with regards to the public's perceptions of UAM vehicles. The study presented in this paper incorporates segregated travel times (In-Vehicle Travel Time and Out-of-Vehicle Travel Time), income categories in the model, and other significant variables like the number of transfers. Additionally, the simulation of alternate trip modes in the model calibration and demand estimation (or model application) is improved by using Application Programming Interfaces (API) (Open., 2019), which uses real trip data for estimating the trip characteristics with high accuracy. Moreover, the parking cost is calculated by developing a function based on economic density and monthly parking costs (Parkwhiz, January 7, 2019). The transit cost calculation is improved by including mode-based, OD cost functions built upon fare charts of respective transit agencies (SF Bay., 2018). The resolution of the analysis is also refined from census tract to census block-group to improve accuracy.

3. Study area

Northern California, centered on San Francisco, was defined as the study area for this analysis, given its UAM potential for commuting trips. Specifically, the success of the UAM depends on the performance of other modes in the region. The San Francisco Bay Area ranks consistently in the top five congested cities globally (Brock, 2018). During peak hours, commuters in the San-Francisco area have lost nearly five days every year to traffic congestion (Dishbrow, 2019). The region's unique polycentric commuting pattern commutes by ground modes in peak hours even more difficult (Miller, 2015). Also, UAM could be affordable to a high portion of the population as the Bay area has the second-highest household income levels in the United States, second only to Washington DC (Vital., 2019), and also has around 640,000 households with an annual household income greater than $100k (CEDDS, Woods and Poole, 2016).

The weather in Northern California also benefits the UAM mode with reduced inclement weather events. Inclement weather conditions can prevent the operation of UAM, similar to the operation of air transportation today. Even with advanced avionics and automation, it would be challenging to provide reliable passenger service in poor weather conditions. Using 11 years of aggregated weather data from National Climate Data Center (NCDC) (Global., 2007–2017) and 1-min weather records by National Oceanic and Atmospheric Administration (NOAA) (ASOS 1-min weather records by NOAA, 2015), it was found that on average, the San Francisco metro area receives only 16 in. of precipitation annually and has zero days of snow with more than an inch. However, San Francisco is impacted by wind, where 16% of the time the wind is above a 15-knot speed between 8 AM-6 PM (ASOS 1-min weather records by NOAA, 2015), fog and seismic activity could affect the operation of a UAM system. The promising commute patterns, population demographics, and generally, favorable weather conditions compared to other U.S. regions support Northern California's selection to investigate UAM operations.

In total, the study area consists of 17 counties (7106 block-groups) centered around the San Francisco area. The selection of counties in the study area matches the range of proposed UAM aircraft, where counties with population centroid within 150 miles of any of the Bay Area cities (San Francisco, San Jose City, Oakland) were selected. Fig. 1 shows a map of the study area. No commuting trips from the county areas outside of the 150-mile radius were considered in this study.

4. Data and methodology

This study includes two tasks. The first was calibrating the mode choice model to quantify how commuters make decisions given the mode alternatives available to them and those alternatives' attributes. The second was applying the mode choice model to all of the commuters in the study area. In the application, the vertiports are first placed, and then the UAM demand for the region was quantified for the given set of vertiports. Table 1 summarizes the datasets supporting the tasks.

4.1. Mode choice model calibration

To estimate the demand for UAM, the mode choice decision-making process of commuters must be understood. This involved reconstructing each individual's mode alternatives choice set (i.e., modes available to them) and estimating how trade-offs are made between attributes of those alternatives such as time and cost. For the mode choice model, we calibrated a mixed conditional logit model. The conditional logit model is a type of logit model that only includes independent variables that vary between the modes for a single commuter (called generic variables- e.g., travel time, cost, distance). Alternative-specific variables that do not vary, such as

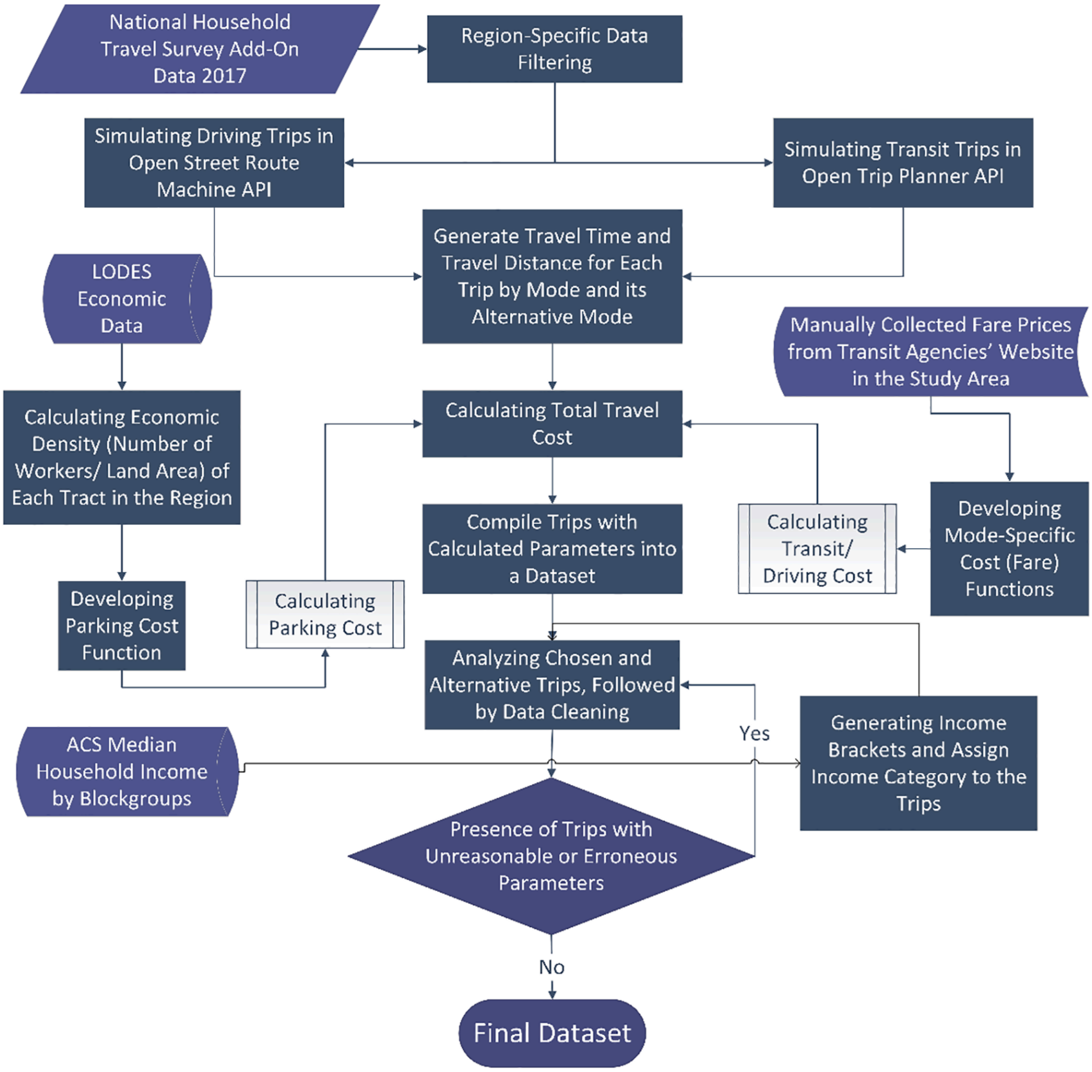

Fig. 2. Framework used to prepare the survey data for model calibration.

number of household vehicles, could not be included because the coefficients for the UAM mode cannot be estimated as it is never the chosen mode in the study's revealed-preference mode choice dataset.

McFadden formulated the conditional logit analysis in detail (McFadden and Zarembka, 1974), which became a popular method for mode choice studies in transportation, including (Li and Kamargianni, 2018; Li and Sheng, 2016; Ashiabor, et al., 2007; Larranaga et al., 2017). However, there are certain limitations to the conditional logit model. It assumes the same preferences for all individuals, which depend only on observable characteristics. The Independence of Irrelevant Attributes (IIA) property of the conditional logit model causes proportional substitution between the alternatives. The mixed logit model overcomes these limitations by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009). In mixed conditional logit models, a commuter is expected to make mode choice decisions based on the utility derived from the mode. The utility that individual n derives from choosing alternative j on choice occasion t is given by $U_{njt} = \beta_n^{'} x_{njt} + \varepsilon_{njt}$ (Hole, 2007), where $\beta_n^{'}$ is a vector of individual-specific coefficients, x_{njt} is a vector of observed attributes relating to individual n and alternative j on choice occasion t, and ε_{njt} is a random term that is assumed to be an independently and identically distributed extreme value. For known β_n, the probability of individual n choosing alternative i on choice occasion t is given by Eq. (1), which is standard conditional probability.

$$L_{nit}(\beta_n) = \frac{\exp\left(\beta_n^{'} x_{nit}\right)}{\sum_{j=1}^{J} \exp\left(\beta_n^{'} x_{njt}\right)} \tag{1}$$

The unconditional probability of the commuter's observed sequence of choices is obtained by integrating L_{nit} over the distribution of β, given by Eq. (2).

$$P_n(\theta) = \int S_n(\beta) f(\beta|\theta) d\beta \quad (2)$$

where:

$$f(\beta|\theta) = density\ for\ \beta,\ where\ \theta\ are\ the\ parameters\ of\ the\ distributions$$

$S_n(\beta_n)$ is the probability of the observed sequence of choices for known β_n and is given by Eq. (3), where $i(n,t)$ denotes the alternative chosen by individual n on choice occasion t and T is the total number of choices.

$$S_n(\beta_n) = \prod_{t=1}^{T} L_{ni(n,t)t}(\beta_n) \quad (3)$$

The coefficients are estimated by maximizing using a log-likelihood maximizing methodology dependent on characteristics of the trip when using that mode. The log-likelihood of the mixed logit model is given by $\mathrm{LL}(\theta) = \sum_{n=1}^{N} \ln P_n(\theta)$, where N is the number of individuals. It is approximated using the simulation method because it cannot be solved analytically. The simulated log-likelihood is then given by Eq. (4), where R is the number of replications and β^r is the rth draw from $f(\beta|\theta)$.

$$\mathrm{SLL}(\theta) = \sum_{n=1}^{N} \ln\left\{ \frac{1}{R} \sum_{r=1}^{R} S_n(\beta^r) \right\} \quad (4)$$

The mixed conditional logit was estimated using the National Household Travel Survey (NHTS) add-on data. Since the NHTS data contains multiple trip purposes and the focus of this study was solely on commuting trips, the following filters were applied to the NHTS data trips. A trip was only included in the study if it: 1) Started and ended inside the study area, 2) Linked home to work or vice-versa, 3) Occurred on a weekday, and 4) Was not completed by walking or biking. Therefore, the trips included either chose auto or transit.

It is important to note that only the chosen mode is reported in the NHTS data, and the unchosen modes had to be generated. Also, some of the travel survey responses were suspicious (e.g., fare paid, travel time) as this is manually reported by the survey respondent and prone to human error. To overcome this data limitation, fare, mileage cost, and parking costs were collected separately for all samples in this study. Fig. 2 and the following sections describe in detail how the data was cleaned and supplemented with data that had an automated collection.

4.1.1. In-vehicle travel time and out-of-vehicle travel time

Driving trips, including the unchosen driving alternatives for chosen transit trips, were simulated in Open Street Routing Machine (OSRM), which is an API built upon the open-source database of OpenStreetMap (OSM) (OpenStreetMap., xxxx). It provided unimpeded IVTT travel time, travel distance, and routes between the OD pair. The unimpeded IVTT travel time was further adjusted using the Texas Transportation Institute Congestion Indices (Report, 2018) to consider the impact of congestion. Travel time index (TTI) is a comparison between the travel conditions in the peak period to free-flow conditions (Traffic., xxxx). The Congestion Indices are published by urban areas, where for example, the congestion factor for the San Francisco-Oakland area is 1.41, and San Jose is 1.38. For the driving alternative OVTT, a constant 3-min OVTT was assumed.

Transit trips, including the unchosen transit alternates for chosen driving trips, were simulated in the Open Trip Planner (OTP) server. It is based upon a transit network built using General Transit Feeds Specifications (GTFS) from 52 transit agencies across the study area. The distribution of walking access distance was generated from the simulation output of the chosen transit trips in the NHTS data, and the 95th percentile of the distribution was selected as the reasonable walking distance to access the transit stations. Separate thresholds were estimated for heavy transit systems (commuter rail, subway) and light transit systems (bus, tram) as it is believed that people travel farther to access heavier modes (Burke and Brown, 2007). The park-and-ride option was simulated for trips with the nearest heavy-rail mode station further than the reasonable walking distance. Transit alternatives involving more than three transfers or with a walking distance more than the reasonable walking distance for transit trips were considered infeasible and therefore discarded. The OTP simulation output included the travel time, distance, and travel mode for every segment of the trip. IVTT was then calculated by adding the time inside the transit vehicles or auto (in case of auto access trips). OVTT was calculated by adding time walking to the station, waiting at the station, walking between stations, and walking to the destination from the station.

4.1.2. Travel cost

The driving cost was calculated using the AAA cost per mile (AAA, 2019) for a Sedan with an annual mileage of 15,000 miles, which was $0.60 per mile. For parking, costs vary drastically inside the central business districts and throughout the study area. Therefore, a constant parking cost was not suitable for all driving trips. Since no public datasets for parking costs were available, we developed a method to estimate the parking costs in the study area. After analyzing the parking rates provided by BestParking by Parkwhiz (Parkwhiz, January 7, 2019) for different urban regions inside the study area, we defined a relationship between economic activity and parking fares. The number of workers per square mile was extracted from the LODES-2015 data at the census tract level to quantify economic activity. Monthly parking rates were manually collected at the census tract level, and a function was generated to calculate the parking cost given the worker density of the census tract. Parking costs for the driving trips were calculated according to the work location's census tract.

For transit, costs provided by the OTP API were often incomplete and used single-trip fares. For this study, it was assumed that

Table 2
Transit cost functions.

Transit Sub-Mode	Fixed Cost ($)	Per-Mile Cost ($)
Commuter Rail	1.60	0.079
Subway	3.10	0.086
Bus	1.823	0.158
Light Rail (Tram)[1]	1.823	0.158
Ferry	6.0	–
Cable Car	2	–

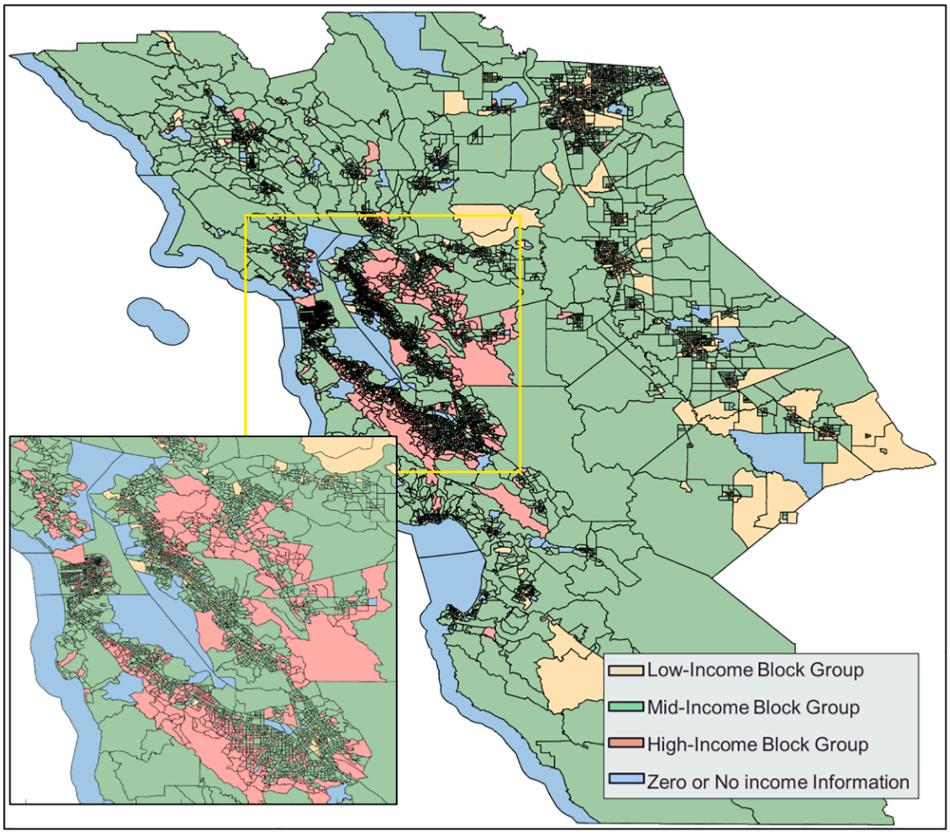

Fig. 3. Income distribution using income categories in the study area.

transit commuters purchase monthly passes[1] for transit trips if offered by the agency; otherwise, a distance-based cost function was used. We developed transit cost functions for all major modes based on the region's transit costs for subway, commuter rail, bus, light rail, ferry, and cable car. We manually collected the transit fares for representative agencies in every transit sub-mode and generated a distance-based cost function using linear regression (see Table 2). Since the OTP API output has detailed information about the distance traveled in every segment of the trip, the transit cost is cumulative of costs incurred during every segment of the trip using the cost functions developed. For Park-and-Ride transit trips, a parking cost is added, which is half of the corresponding driving parking cost in the census tract of the origin transit station because parking at transit station is often subsidized to promote public transit use.

[1]Light Rail and Bus services are usually provided by the same agency and follow a similar fare structure

4.1.3. Income categories

Besides attributes of the mode, the mode-choice is also influenced by the individual's characteristics, such as their Value Of Time (VOT). In transportation, the value of time for commuting is often estimated for different income levels as it is assumed that high-income individuals have a higher value of VOT than low-income individuals (Börjesson et al., 2012). Due to the lack of records in the NHTS data, full segmentation, i.e., separate models for different income categories, was not feasible. Therefore, a partial segmentation (i.e., including variables interacting cost with income bins) was employed to account for the impact of income on an individual's mode choice.

[1] Transit agencies monthly passes costs were either fixed or distance-based on origin–destination zones.

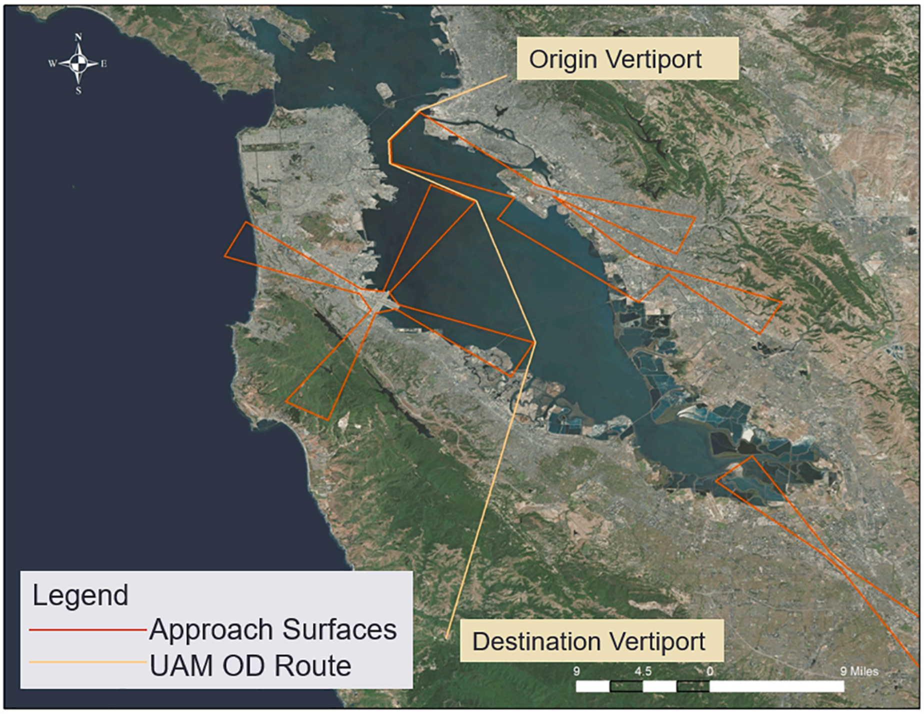

Fig. 4. Example of a UAM OD route avoiding approach and departure surfaces of precision runways at commercial airports.

The model included three income categories, *Low-Income, Mid-Income,* and *High-Income*. The brackets were estimated using the 30th percentile ($45,000) and the 90th percentile ($152,000) of the household income distribution in the region (Reeves, 2018). Since the LODES data lacked income information, the home block-group's median household income was used as an indicator. This information was extracted from the 2017 ACS 5-year estimates[2]. The block-group level was the finest resolution at which median household income is reported. Fig. 3 shows the income distribution in the study area based on the categories employed in the analysis.

4.2. Model application

The calculation of UAM demand was an integrated process that worked in conjunction with the placement of vertiports. We developed an algorithm that used the calibrated mode choice model to place the vertiport in a way to maximize UAM demand for a given number of vertiports in the region. This model application used LODES-2015 data at the block-group level to estimate the number of commuting trips. The home block-group was the origin, and the work block-group was the destination for the home-to-work trip and vice-versa for the work-to-home trip. The commutes were then simulated to gather the trip characteristics needed to apply the mode choice model. The driving trips were simulated using the OSRM API, and transit trips were simulated using the OTP API. The UAM alternative was added to the mode choice set by considering both accessing the vertiport and the UAM trip itself. The access part of the trip was assumed to be completed by walking if the vertiport was within reasonable walking distance from the location. Walking time was estimated assuming an average walking speed of 3.1 mph; otherwise, the trip was simulated in OSRM API with taxi/cab characteristics. Similar assumptions were made for traveling from the destination vertiport to the final destination. In addition, the ingress and egress times were assumed to represent the out-of-vehicle time spent at the vertiport (ticketing, boarding, and alighting the UAM vehicle). The UAM part of the trip was simulated on the designated path, which was designed to avoid protected commercial airspace keeping a minimum distance between OD. Fig. 4 shows an example of a UAM OD route avoiding approach and departure surfaces of precision runways at commercial airports in the Bay Area. Therefore, the total UAM trip travel time consisted of the following five parts; walking or taxi time to get to vertiport from origin location, ingress time (five-minutes), UAM flight time, egress time (five-minutes), and walking or taxi time to get to the final destination. Table 3 outlines the assumptions made for the UAM alternative.

The probability of each available mode was calculated for every origin–destination (OD) pair in the LODES data. There were 4.63 million daily commuters inside the study area sharing 2.3 million OD pairs. Applying the mode choice probability and the total number of trips between the OD pair, the mode-specific demand was calculated. The total UAM demand was calculated by combining the UAM demand for all OD pairs.

The UAM demand analysis required the number of vertiports and UAM CPM value as inputs. For this study's purposes, vertiports are assumed to be open to operation 24 h a day, 7 days a week. The framework for vertiport placement is shown in Fig. 5. The process

[2] Table B19013: Median household income in the past 12 months (in 2017 inflation-adjusted dollars)

Table 3
Assumed parameters for UAM trip calculations.

Parameter		Value
Walkable Distance To/From Vertiport		0.40 mi
Ingress[1] Time		5 min
Egress Time		5 min
Average UAM Vehicle Speed		120 mph
Average Walking Speed		3.1 mph
Minimum Trip Distance for UAM Eligibility		10 miles
Taxi/Cab Fare Structure ($)	Base Fare	2.20
	Per Minute	0.42
	Per Mile	1.60
	Service Fee	1.70
	Minimum Fare	7.20

[1] Ingress/Egress times account for processing and boarding/alighting the vehicle at the vertiport. They do not account for trip delays.

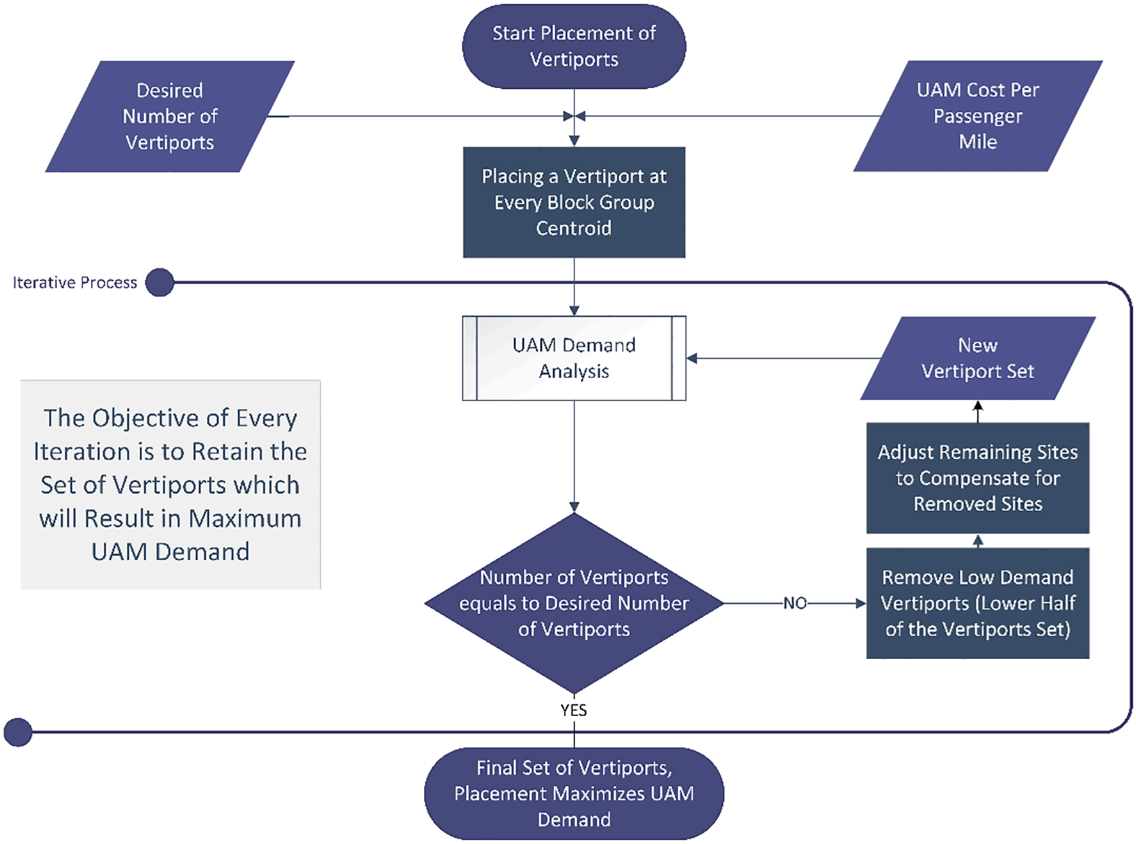

Fig. 5. Placement of vertiports workflow.

started with the highest resolution, i.e., placing a vertiport at each block-group centroid in the region. Every blockgroup has a vertiport assigned to it (closest to the blockgroup centroid). In each iteration, the mode choice model was used to calculate the UAM demand at each vertiport. At the end of the iteration, the vertiports set was sorted by descending UAM demand, and only the vertiports in the upper half of the set were retained. The location of some of the retained vertiports was modified to accommodate for the demand generated from blockgroups that lost their assigned vertiport in the last iteration. The iterations were stopped when the number of vertiports reached the desired number of vertiports. After the final iteration, vertiports in high-demand areas are generally found at blockgroup centroids, whereas vertiports in low-demand areas are generally found at the demand weighted mean of multiple blockgroup centroids. For this study's purposes, it is assumed that these final vertiports have the number of parking stalls and vertipads needed to serve all demand (i.e., the demand does not exceed the capacity). The sizing of vertiports is outside the scope of this study.

Table 4
Model variable definitions.

Variable	Definition	Unit
IVTT	In-vehicle travel time: time spent in a motorized vehicle, such as auto, subway train, or UAM aircraft	Minutes
OVTT	Out-of-vehicle travel time: time spent out of a motorized vehicle, such as walking or waiting	Minutes
Cost	Monetary cost: includes costs such as transit fares, fuel costs, parking costs, etc.	$
Transfers	Number of transit-to-transit transfers on the route. Driving-to-transit or transit-to-driving do not count as transfers.	Transfers
Low Income	Income less than 30th percentile for the region (<$45,000)	Binary
Medium Income	Income between 30th and 90th percentiles for the region ($45,000-$152,000)	Binary
High Income	Income greater than 90th percentile for the region (>$152,000)	Binary

Table 5
Mode choice logit model.

Variable	Coefficient	Standard Error	z	P>|z|	95% Conf. Interval
Mean					
IVTT	−0.0517868	0.0000147	−1823.47	0.000	[−0.0518, −0.0517]
OVTT	−0.0901427	0.0000129	−3529.78	0.000	[−0.0902, −0.0901]
Transfers	0.3857525	0.000195	−4606.01	0.000	[0.3853, 0.3861]
Ln(-Low Income × Cost)	−1.059794	0.000201	1977.81	0.000	[−1.0601, −1.0593]
Ln(-Medium Income × Cost)	−1.214655	0.0001078	−5252.23	0.000	[−1.2148, −1.2144]
Ln(-High Income × Cost)	−1.689608	0.0004159	−1.1000	0.000	[−1.6904, −1.6887]
Transit Constant	−0.6572835	0.0003605	−4062.82	0.000	[−0.6579, −0.6565]
Standard Deviation					
Lognormal Std. Dev. (−Low Income × Cost)	0.0014603	0.0004115	3.55	0.000	[0.0006, 0.0022]
Lognormal Std. Dev. (−Medium Income × Cost)	0.3733613	0.0001538	2426.96	0.000	[0.3730, 0.3736]
Lognormal Std. Dev. (−High Income × Cost)	1.119758	0.0006354	1762.43	0.000	[1.1185, 1.1210]
Median IVTT VOT (per hr.)	$8.97, $10.47, $16.83				
Median OVTT VOT (per hr.)	$15.7, $18.22, $29.30				
Number of estimated parameters	10				
Log-likelihood$_{Initial}$	-2.42×10^{8}				
Final Log-likelihood$_{Final}$	-2.3×10^{8}				
Likelihood chi-square test statistic (Degree of Freedom:3)	6349661.4				
Number of observations	10,012				
Prob > χ^2	0.0000				

5. Calibrated mode choice model results

The selection of variables in the model was influenced by both prediction power and data capabilities. For data capabilities, variables that were in the NHTS mode-choice data but not in the LODES application data could not be included in the calibrated mode choice model. Table 4 includes the variables which resulted in the best fit for the calibrated model. In the final model, the income and cost variables interacted in order to allow for income to be incorporated as income by itself is an alternative-specific variable. The income interacted cost variables were then randomized to account for heterogeneity in the data. The negative sign of the income interacted cost variables is required for reasonable UAM demand estimation. If the mode choice analysis is performed with a positive coefficient for travel cost, an unreasonably high probability is observed for the UAM mode in mid to long-distance trips. The lognormal distribution was selected to avoid such infeasible demand estimates. The unavailability of variables related to traveler's characteristics in application data restricted us from capturing heterogeneity due to traveler's characteristics in the model. The number of steps for simulation in both model calibration and demand estimation was kept at 100 because there was a negligible improvement in model fit above 100.

Table 5 presents the coefficients for the mixed conditional logit mode choice model for Northern California. The model is statistically significant because the p-value is less than 0.000. The model includes both IVTT and OVTT coefficients, the number of transfers required for the trip, and interactions between the trip cost and the traveler's household income. Validation of mode-share by distance is included in the Appendix (Figs. 10–12).

Since UAM was not available in Northern California during the 2017 NHTS data collection, there was no revealed-preference data for the mode. This means that the UAM mode constant could not be estimated on the NHTS data. Instead, the UAM constant needed to be computed based on a stated-preference survey that captures the population's willingness-to-pay for the UAM mode. There are several UAM stated-preference surveys in literature, including (Boddupalli, 2019) (used in this study) and (Eker et al., 2020).

To create our mode choice model, we first calibrated a mixed logit model using a lognormally distributed sampling of the income interacted cost variable. The distribution was bounded by the 5th and 95th percentile. This revealed-preference (RP) model had a transit constant with drive alone as a reference alternative, as shown in Eq. (5). This model did not include a UAM constant as this mode is not an existing commuting alternative. V_{RP} is the estimated utility for the i^{th} commuter to take mode alternative j.

$$V_{RPij} = \beta_1 X_{ij} + \beta_2 X_{ij} + \cdots + \beta_n X_{ij} + \varepsilon_{RP\_Transit} \tag{5}$$

Next, to transfer the constants, Dr. Garrow's research group calibrated a model on stated-preference (SP) survey data (Boddupalli, 2019) using the same model methodology, sampling distribution type, and variables as the RP model. The exact SP model we requested

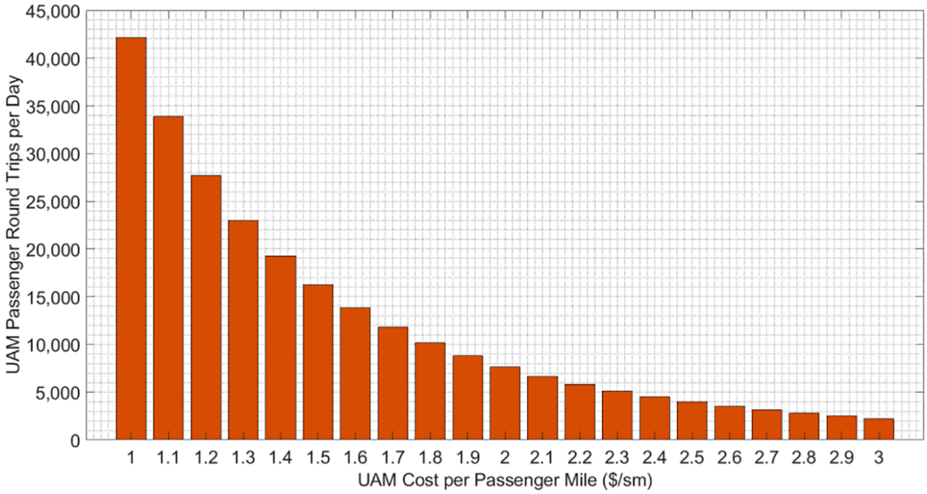

Fig. 6. Daily UAM demand sensitivity to CPM (75 Vertiports).

from Dr. Garrow's research group (variables and estimation method) is not in the thesis (Boddupalli, 2019). It is important to note that the RP model was estimated only on Northern California travel behavior. The SP surveys were distributed across 5 U.S. cities. The Northern California income breaks would not be the same for the five regions, given the cost of living differences. Therefore, the SP model includes a continuous income variable. As shown in Eq. (6), this model included the constants of transit and drive alone, with UAM as the reference alternative.

$$V_{SP_{ij}} = \beta_1 X_{ij} + \beta_2 X_{ij} + \cdots + \beta_n X_{ij} + \varepsilon_{SP\_Transit} + \varepsilon_{SP\_DriveAlone} \tag{6}$$

The probabilities calculated from mixed logit models are driven by the differences in utilities between the available modes. Therefore, it was important to preserve the differences in constants from the SP model when creating the UAM constant in the RP model. Due to scalability between models, the differences between the SP constants were transferred by translating to an equivalent in-vehicle travel time utility. This followed the constants transferability method proposed by Cherchi et al. (Cherchi and de Dios Ortúzar, 2006). This made UAM is the new reference alternative in the RP model. Unfortunately, due to IRB restrictions, we were unable to calibrate an RP-SP pooled model, which could provide us the scaling parameter. Therefore, we resorted to the method presented in Chen and Naylor (Chen and Naylor, 2011) where authors estimated the Bus Rapid Transit (BRT) constant for an RP-based model using the constants from an SP-based market research model. The constant coefficients are converted into bias time constants by dividing the constant-coefficient by the in-vehicle time coefficient.

$$b_m = \frac{c_m}{c_{\text{ivtt}}} \tag{7}$$

where b_m is bias time constant for mode m; c_m is constant-coefficient for mode m and c_{ivtt} is the in-vehicle travel time coefficient in the SP model. The bias time constants derived from the SP model were used in the estimation of UAM constants for the RP model. The UAM constant was calculated by a linear interpolation method using the auto constants, transit constants, and bias time constants estimated.

$$\Delta_{UAM} = \Delta_{PT} + (\Delta_{Auto} - \Delta_{PT})\left(\frac{b_{UAM} - b_{PT}}{b_{Auto} - b_{PT}}\right) \tag{8}$$

where Δ_{UAM} is UAM constant, Δ_{PT} is public transit constant, Δ_{Auto} is auto constant in the RP model; b_{UAM} is UAM bias time constant, b_{PT} is public transit bias time constant, and b_{Auto} is auto bias time constant. Δ_{UAM} was estimated to be 0.020569.

In this study, the SP data was not accessible for this study, so additional comparisons and statistical tests between the SP data and RP data could not be performed, such as in Washington et al. (Washington et al., 2020). Therefore, while this study's methodology for transferring constants from an SP survey to RP application aligned with the literature, this study was limited in the detailed comparison of the underlying data of the models.

6. Demand model application results

The calibrated mode choice model, including the calculated UAM constant, was applied to Northern California commuting trips. Fig. 6 outlines the sensitivity of demand with respect to the CPM offered by the UAM operating agency, assuming a constant 75 vertiports in the region. At a $1 CPM, there is a 42,140 UAM round trip demand per day, where increasing the CPM by just 20 cents reduces the demand by 34%. The sensitivity analysis results provide supportive evidence that a low offered CPM is required for the system's success. The reduction in demand for higher CPMs reduces the revenue significantly and prevents the mode from covering fixed costs such as vertiport land and maintenance costs.

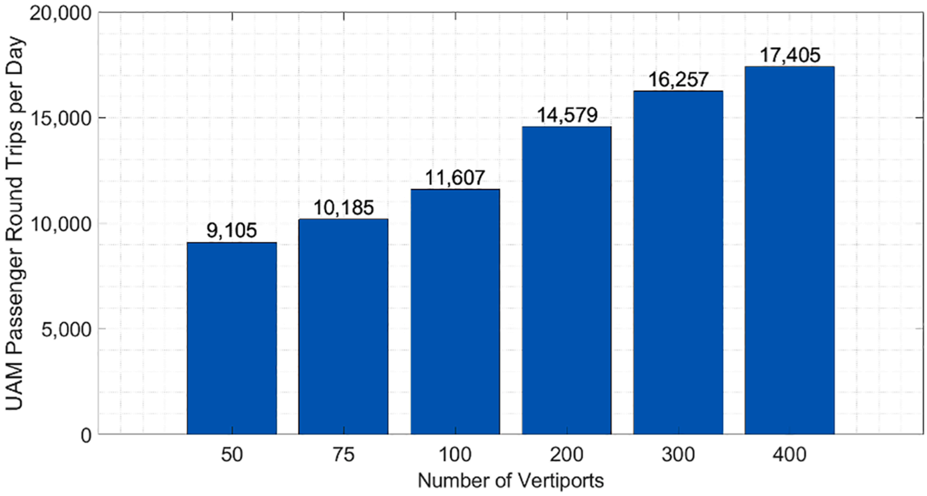

Fig. 7. Daily UAM demand sensitivity to number of vertiports ($1.80 CPM).

Fig. 7 illustrates the sensitivity of demand when the number of vertiports is changed, keeping the CPM at a constant $1.80. The vertiports for each scenario (e.g., 50, 75, 100 vertiports) are placed to maximize the UAM demand for a given number of vertiports in an iterative manner. To clarify, the vertiports location in the 50-vertiport set is not necessarily a subset of a larger vertiport set. As the number of vertiports increase, there is a direct relationship with the number of commuters in the catchment area, which increases the demand for the mode. It is evident that there are core vertiports that serve the majority of the demand and feeder vertiports that provide UAM service in lowered demand areas. Comparing the 50 vertiport and 400 vertiport scenarios shows that reducing the number of vertiports by 87.5% reduces the demand by 47%. This concentration of demand at a small portion of the vertiports is similar to the current airport system in the United States with hub airports and regional airports. However, at a closer look, it becomes evident that a large number of vertiports is not economically viable for Northern California at a $1.80 CPM. For the 400 vertiport scenario, 196 of the vertiports have a demand of fewer than 50 UAM operations[3] per day.

The following sections analyze UAM demand further by evaluating two scenarios: 1) A high demand scenario with a large number of vertiports and low CPM (200 vertiports at $1.20) and 2) A low demand scenario with a small number of vertiports and high CPM (75 vertiports at $1.80). These two scenarios are used to provide a sensitivity analysis of demand and do not necessarily estimate the upper and lower bounds for demand in the region as it is possible that the UAM system, if built, would have to exceed a $1.80 CPM to recover costs. In both scenarios, vertiports are placed in an iterative manner, explained in Section 4.2.

6.1. High demand scenario (200 vertiports, $1.20 CPM)

To generate the high demand scenario, a 200 vertiport system offering trips at $1.20 CPM was estimated. Fig. 13 shows the vertiport placement that maximizes the person-trip demand for this scenario in an iterative manner. It is shown that the areas with a higher concentration of vertiports have both a high worker density, high population density, and a high median income. An example of this is the Central Business District (CBD) of San Francisco, shown in Fig. 13′s inset. There are around 514,000 employees in San Francisco CBD and 196,000 people who live there (87,000 of which are employed inside CBD) (U.S.Census., 2018). Due to such a high concentration of work locations and households in CBD, the high demand vertiports are nearby.

The busiest vertiport is estimated to have 5740 UAM operations per day. The Financial District is a big attractor of UAM trips because of the work location density and heavy disutility in driving due to parking rates and congestion. Unfortunately, the departure time information for application data was missing. To reflect the true nature of commuting trips, commuters' departure time distribution was extracted from NHTS data. Using that cumulative density function, the total person-trips between each OD pair were distributed over the day. Of that 5740 UAM operations, 61% are expected to occur during the core commuting hours, between 6 AM – 9 AM and 4 PM – 7 PM.

There are more than ten vertiports placed with significantly high demand in the San Francisco CBD using the demand-driven approach. In the future, if the system increases to higher demand levels, it could be challenging to manage the peak-hour demand as it is concentrated in a small area from the perspective of airspace service providers. Moreover, results suggest that demand is very one-directional, where morning peak hour trips are into the city centers such as the San Francisco CBD, Mountain View, Cupertino, and the San Jose CBD, and the afternoon peak hour trips leave these city centers. This suggests that the commuter UAM system will require a large proportion of deadheading, where the aircraft will fly at times with a zero load factor. From Fig. 3, the high-income areas can be

[3] UAM operation means a landing or a take-off. UAM operations are estimated from UAM passenger trips assuming 60% load factor or 2.4 passengers per flight.

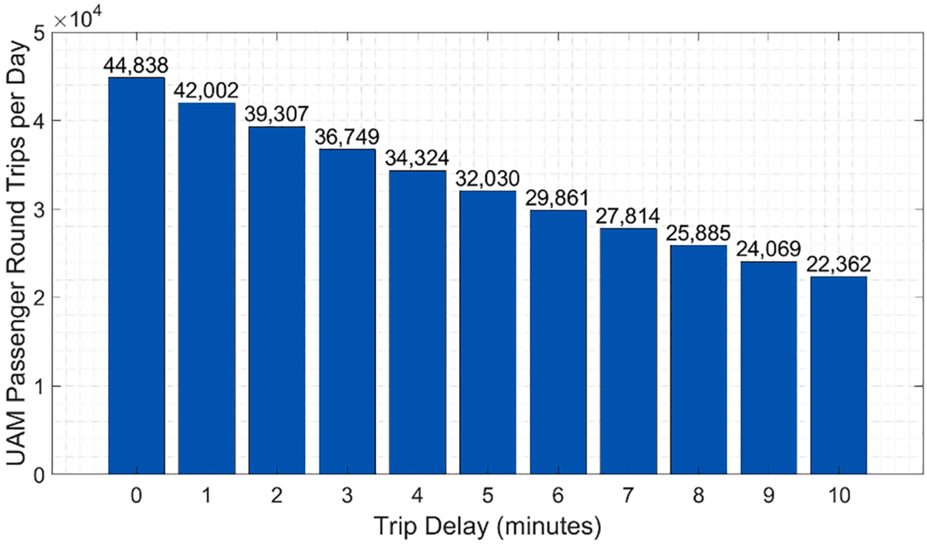

Fig. 8. Sensitivity of UAM demand with person wait time.

observed around the bay and areas North-West of Oakland. It is evident that most of the feeder vertiports are placed in these areas, thereby reinforcing the influence of high-income earners on vertiport location when vertiports are placed for maximum UAM demand in an iterative manner.

Our analysis assumes a 5-minute ingress and 5-minute egress time of the UAM vehicle as well as a 0-minute delay waiting for the UAM vehicle to arrive. Fig. 8 shows that UAM commuting demand is highly sensitive to any delay in the system, where the demand is cut in half by adding 10 min of delay. This inability for the system to take delay provides supportive evidence that for commuting purposes, the UAM system will either need to: 1) have low load factors as there is little time to group people up with the same OD pair or 2) rely on advanced trip bookings to group passengers resulting in a scheduled departure time that ideally would not be delayed.

6.2. Low demand scenario (75 vertiports, $1.80 CPM)

UAM is expected to be a costly mode and, therefore, will cater more towards higher-income households. Results indicate that the market share of high-income households will increase as the CPM increases. Specifically, in this low demand scenario, the market share of low-, mid-, and high-income households is 3%, 26%, and 71%, respectively. This is in comparison with the previous high demand scenario, where the low-, mid-, and high-income market shares were 2%, 39%, and 53%. Fig. 14 shows that when the CPM is increased, and the number of vertiports are reduced, the surviving vertiports are located in dense employment areas or household areas with a higher than average income level. The feeder vertiports are cut due to low demand. Also, the largest vertiport in this scenario has 1702 UAM operations, compared to the 5740 UAM operations from the largest vertiport in the high-demand scenario.

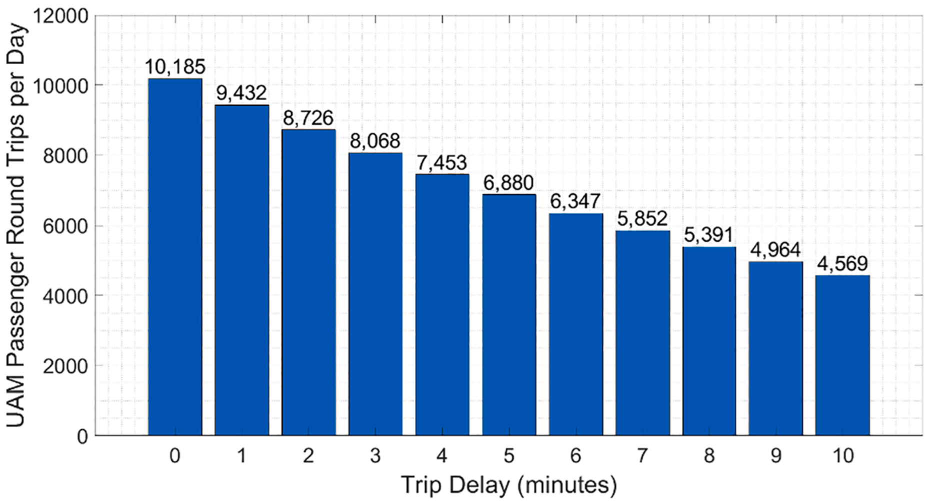

Fig. 9. Sensitivity of UAM demand with person wait time.

Fig. 9 shows that the percent reduction per minute of added delay is similar to that of the high demand scenario, where 10 min of delay reduces the demand by half. This is especially problematic in this low demand scenario, as with 10 min of delay, the system would have to rely heavily on other trip purposes to cover the system costs as it is estimated there is only a 4569 commuting roundtrip demand total for the Northern California region.

7. Conclusions and policy implications

This study provided a sensitivity analysis of UAM demand in Northern California solely for commuting purposes. It considered the mode alternatives of UAM, drive alone, and transit. Findings include that, first, the UAM mode's success is hugely dependent on the mode's popularity with travelers in the high-income market segment. Therefore, it is essential for UAM to be a competitive mode for these travelers and to increase their level of trust and comfort in the system.

Also, the success of UAM is dependent on the operational efficiency of the system. Even without accounting for deadheading and higher fares levels due to vertiport costs, the demand is small, and it will be difficult for the system to be profitable on commuting trips alone. It seems this system has to be "errorless" for commuting purpose. The system's efficiency is a top priority as every very minute of additional wait time greatly impacts the mode's demand. The UAM system must have policies that lead to a minimum delay, or else the driving alternative quickly becomes a more attractive mode for commuters.

The construction and operation of a future UAM system will be complex and require intricate long-term planning. Based on our findings, several policies will be needed to promote the system's success and economic feasibility. Many of these policies are implemented in some form for other transportation systems (e.g., aviation or driving), so the lessons learned in their implementations

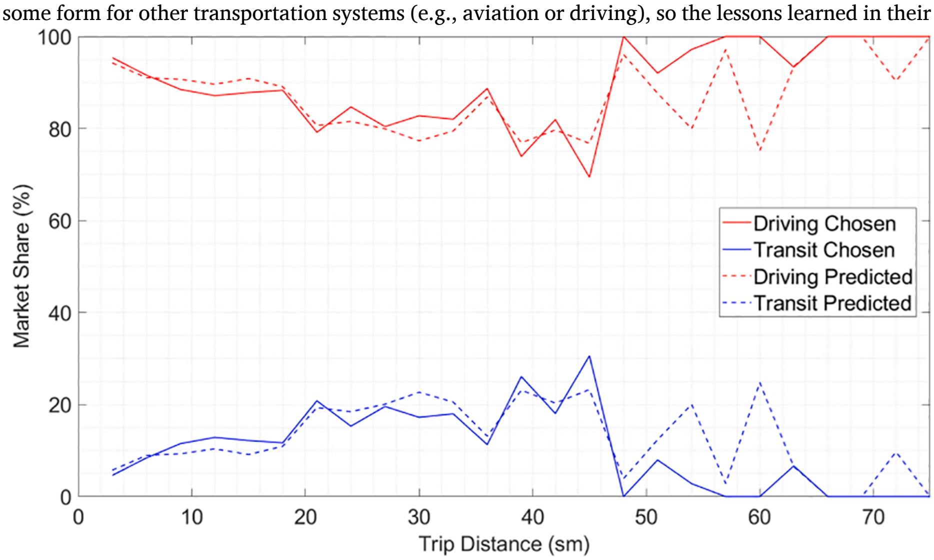

Fig. 10. Market share by distance.

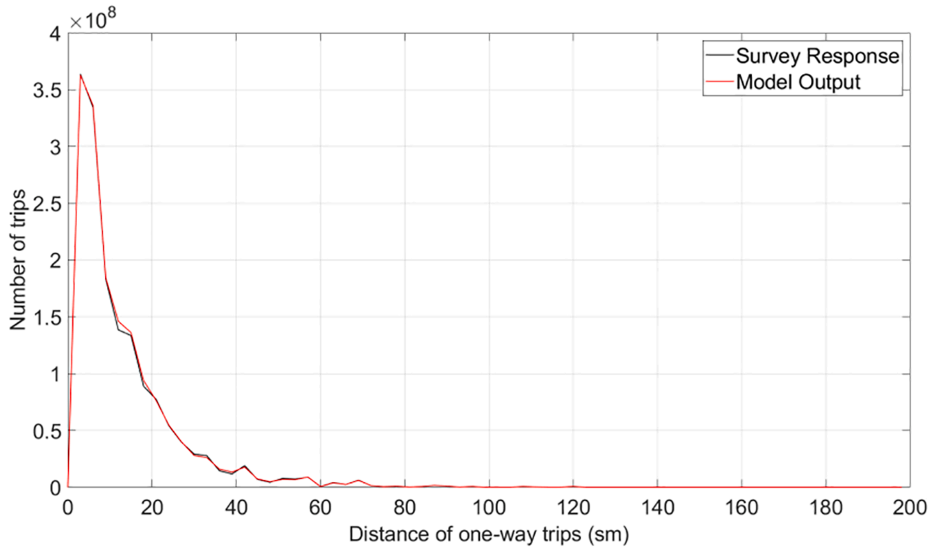

Fig. 11. Comparison of survey responses and model predictions for driving rips.

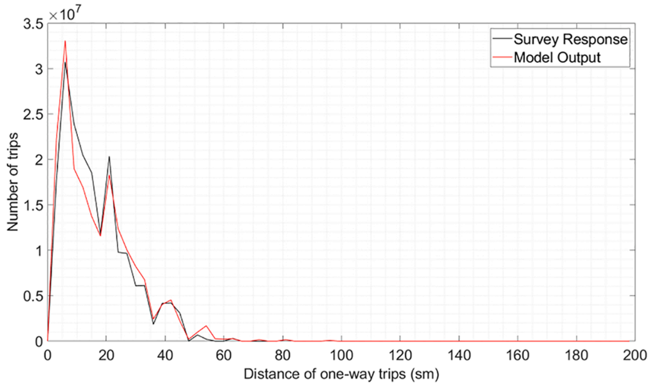

Fig. 12. Comparison of survey responses and model output for transit trips.

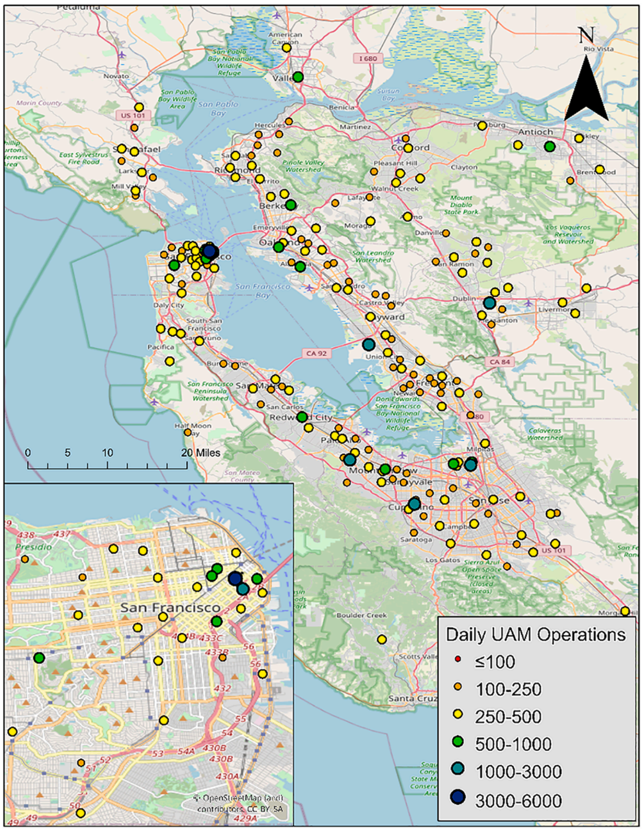

Fig. 13. High demand scenario vertiport placement and demand.

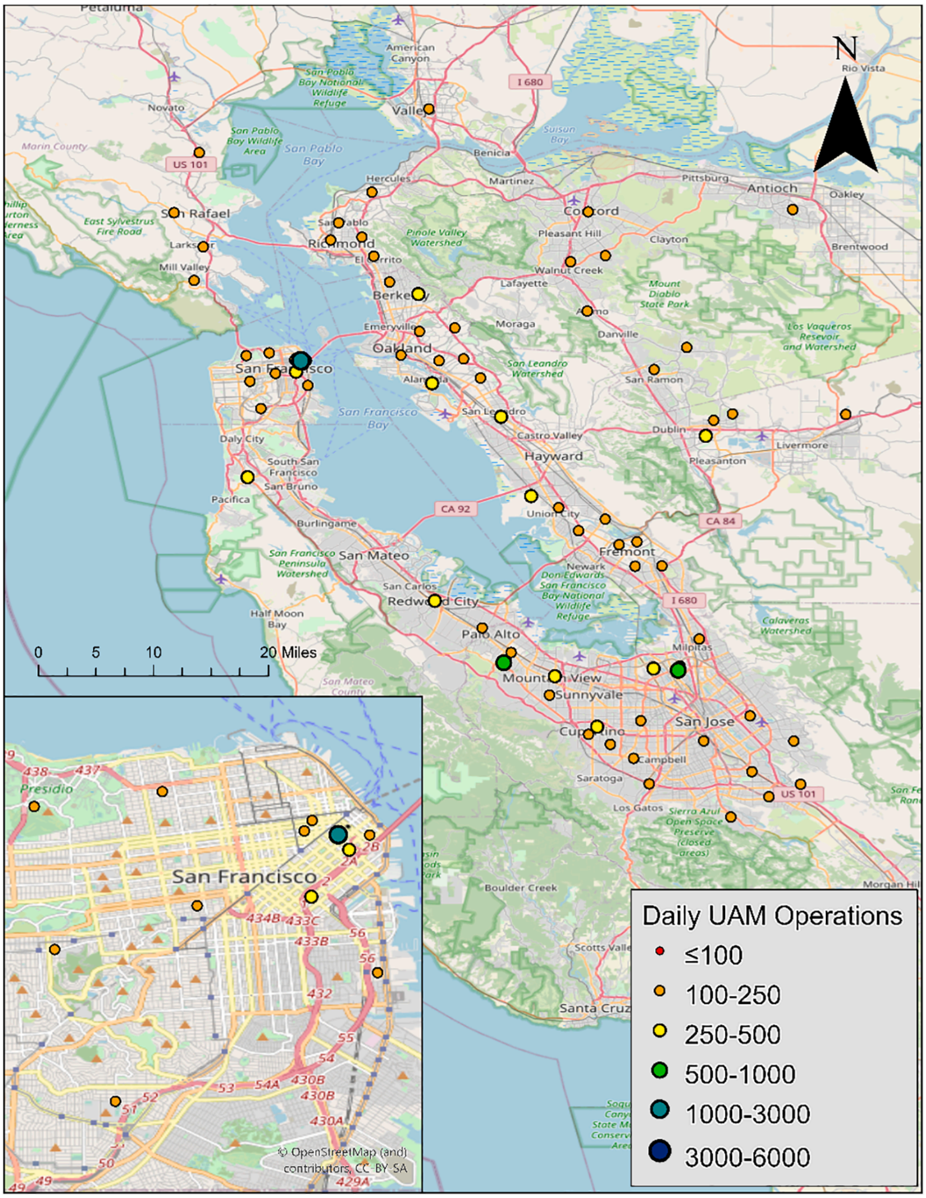

Fig. 14. Low demand scenario vertiport placement and demand.

will be of use to the UAM system.

First, similar to road transportation, UAM commuting demand had morning and afternoon peak hours and is very concentrated in short time periods. Unless other trip purposes can make the UAM demand more uniform throughout the day, operators of the UAM system will need to implement some form of congestion pricing. Otherwise, the system's infrastructure will be overbuilt to serve the peak hours while being mostly empty the majority of the day. There is flexibility in how this congestion pricing would be implemented as the ticket purchase process is unknown at this time.

Second, as stated in the results, not only will UAM have peak hours for commuting, but also each peak hour will be very unidirectional, requiring a significant amount of deadheading. While UAM will be fully electric, policies to reduce energy consumption due to deadheading may need to be implemented. Deadheading is seen in ride-hailing services today, and the effects have been analyzed for environmental impacts. For example, due to increased carbon emissions of ride-hailing, California has proposed regulations on the industry (Barboza, 2020).

Lastly, vertiports with the highest demand are located in downtown areas with limited land available. These two conflicting trends will require similar policies as expanding airports in downtown regions today (land acquisition, noise complaints, etc.). Vertiport constraints are different from airports (e.g., can build on the roof), but the general ideas are the same. Currently, the UAM system is described as being run and operated by a private company (e.g., UberElevate), but this land issue shows the large roles that the government will most likely have in the initial setup of the system. Policies similar to that of expanding airports in downtown regions may need to be considered in building the UAM system.

8. Study limitations and future research

The findings presented in this paper are for scenarios that do not include the impacts of weather conditions on demand and operations, vertiport or airspace capacity issues, additional wait time for deadheading flight to arrive, and reliability issues of UAM. This study assumed ideal conditions in each of these areas. However, adding these factors to the analysis would improve the accuracy of the demand estimation. It is recommended for future region-specific UAM demand models, like the one presented in this paper, to include UAM system capacity as well as customer perception of the UAM system's reliability, safety (Ahmed et al., 2021), and trip experience. Important trip experience factors found in the literature, for example, include "familiarity, value, fun factor, wariness of new technology, fear and happiness" (Winter et al., 2020).

Limited variables could be used in model calibration due to a lack of individual-level information in the application data (LODES). The model application could improve by including variables such as 'number of household vehicle' and 'household size,' which would improve the model's estimation of how travelers access the UAM system. This analysis assumed that the commuter would always choose the closest vertiport to the home/workplace and would either walk (if the distance is less than the walking threshold) or take a taxi to the vertiport. In future research, these assumptions could be relaxed by instilling some probabilistic behavior in vertiport selection and considering more ways to reach vertiport such as drop-off and parking if available.

Similarly, there are multiple routes one can choose from when commuting. The data collected through the OSRM API assumed that commuters take the fastest route available and would travel non-stop to their home or workplace, removing the effects of trip-chaining on UAM demand. This is a limitation that needs to be addressed in the future.

Estimating travel costs for transit connections depended on the transit agencies that involved both distance-based fare structures and flat-rate monthly passes. The flat-rate bias could impact the calibrated model, i.e., increased preference for the service offering flat-rate (monthly passes) instead of pay-per-use. Flat-rate travel cost functions could have caused bias in the public transit coefficient (Wirtz et al., 2015). Although not addressed in this study, flat-rate bias should be considered in future research.

While our study included the effects of Willingness-To-Pay (WTP) with respect to travel time on mode choice, the literature suggests that the value of travel time reliability (VOR) is also a significant factor. When unaccounted for, VOR can impact WTP values (Carrion and Levinson, 2012). Our study used deterministic travel times and, therefore, the WTP values were constrained to be negative. Future studies using stochastic travel times should consider the effects of VOR separately from WTP for travel time savings on mode choice.

Another limitation of the study is the inability to account for dynamic delays that occur in all modes. It used a congestion factor to account for road delays, but considering the dynamic nature of congestion could certainly improve driving time estimation for driving trips and the intermodal connection of UAM trips. Similarly, delays due to UAM charging should also be added to future simulations when this information becomes known about the new technology.

Lastly, future studies should consider additional trip purposes, including personal trips. This would give additional demand to the system without expanding the UAM system infrastructure by increasing trips to the non-peak hours. Adding these trips would provide more justification for the UAM system.

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Appendix

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2021.03.020.

References

AAA: Your Driving Costs https://exchange.aaa.com/wp-content/uploads/2017/08/17-013_Your-Driving-Costs-Brochure-2017-FNL-CX-1.pdf. [accessed July 15, 2019].

Ahmed, Sheikh Shahriar, Fountas, Grigorios, Eker, Ugur, Still, Stephen E., Anastasopoulos, Panagiotis Ch, 2021. An exploratory empirical analysis of willingness to hire and pay for flying taxis and shared flying car services. J. Air Transport Manage. 90, 101963. https://doi.org/10.1016/j.jairtraman.2020.101963.

Al Haddad, C., Chaniotakis, E., Straubinger, A., Plötner, K., Antoniou, C., 2020. Factors affecting the adoption and use of urban air mobility. Transport. Res. A: Pol. Pract. 132, 696–712. https://doi.org/10.1016/j.tra.2019.12.020.

Ashiabor, S. et al., 2007. Development of an Intercity Mode Choice Models for New Aviation Technologies. In Aviation: A World of Growth (pp. 61-77). DOI: https://doi.org/10.3141/2007-01.

ASOS 1-min weather records by NOAA (2015) ftp://ftp.ncdc.noaa.gov/pub/data/asos-onemin/.

Balac, M., Rothfeld, R.L., Hörl, S., 2019. The prospects of on-demand urban air mobility in Zurich, Switzerland. In: 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 906–913). IEEE, https://doi.org/10.1109/ITSC.2019.8916972.
Balac, Milos, Vetrella, Amedeo R., Rothfeld, Raoul, Schmid, Basil, 2019. Demand estimation for aerial vehicles in urban settings. IEEE Intell. Transp. Syst. Mag. 11 (3), 105–116. https://doi.org/10.1109/MITS.511764510.1109/MITS.2019.2919500.
Barboza, T., 2020. Taking an Uber or Lyft pollutes more than driving, California finds. Next stop: Regulations. LATimes. https://www.latimes.com/environment/story/2020-03-07/uber-lyft-ride-hailing-air-pollution-greenhouse-gas-emissions [accessed September 15, 2020].
Behme, J., & Planing, P. (2020). Air Taxis as a Mobility Solution for Cities—Empirical Research on Customer Acceptance of Urban Air Mobility. In Innovations for Metropolitan Areas (pp. 93-103). Springer, Berlin, Heidelberg, https://doi.org/10.1007/978-3-662-60806-7_8.
BLADE, BLADE Urban Air Mobility. https://blade.flyblade.com/p/about [accessed November 1, 2019].
Boddupalli, S.S., 2019. Estimating demand for an electric vertical landing and takeoff (eVTOL) air taxi service using discrete choice modeling (Doctoral dissertation, Georgia Institute of Technology), http://hdl.handle.net/1853/61811.
Booz Allen Hamilton, 2018. Final Report: Urban Air Mobility Market Study. https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20190001472.pdf [accessed September 12, 2020].
Börjesson, M., Fosgerau, M., Algers, S., 2012. On the income elasticity of the value of travel time. Transport. Res. A: Pol. Pract. 46 (2), 368–377. https://doi.org/10.1016/j.tra.2011.10.007.
Brock (2018). https://www.nbcbayarea.com/news/local/san-francisco-worst-traffic-congestion-report/200683/ [accessed 12 July 2019].
Bulusu, V., Onat, E.B., Sengupta, R., Yedavalli, P., Macfarlane, J., 2021. A traffic demand analysis method for urban air mobility. IEEE Trans. Intell. Transp. Syst.
Burke, Matthew and Brown, AL. Distances People Walk for Transport, 2007. Road & Transport Research: A Journal of Australian and New Zealand Research and Practice, Vol. 16, No. 3, 16-29. [accessed July 15, 2019].
Carrion, Carlos, Levinson, David, 2012. Value of travel time reliability: a review of current evidence. Transport. Res. A: Pol. Pract. 46 (4), 720–741.
CEDDS, Woods and Poole, 2016 https://www.woodsandpoole.com/product-category/cedds/.
U.S. Census Bureau, 2015. LEHD Origin-Destination Employment Statistics (2002-2017) [computer file]. Washington, DC: U.S. Census Bureau, Longitudinal-Employer Household Dynamics Program [distributor], accessed on 5th May 2016 at https://lehd.ces.census.gov/data/#lodes LODES 7.4.
Čertický, M., Jakob, M., Píbil, R., 2015. Analyzing on-demand mobility services by agent-based simulation. J. Ubiquitous Syst. Pervasive Networks 6 (1), 17–26. https://doi.org/10.5383/juspn.06.01.003.
Chen, Chun-Hung, Naylor, George, 2011. Development of a mode choice model for bus rapid transit in Santa Clara County, California. J. Public Transport. 14 (4), 1–22. https://doi.org/10.5038/2375-090110.5038/2375-0901.14.410.5038/2375-0901.14.4.1.
Cherchi, E., de Dios Ortúzar, J., 2006. On fitting mode specific constants in the presence of new options in RP/SP models. Transport. Res. Part A: Pol. Pract. 40 (1), 1–18. https://doi.org/10.1016/j.tra.2005.04.002.
Davies, Alex., 2016. Inside Uber's Plan to take Over the Skies with Flying Cars. https://www.wired.com/2016/10/uber-flying-cars-elevate-plan/ [accessed May 4, 2018].
Dishbrow, 2019. https://www.sfgate.com/traffic/article/bay-area-worlds-worst-traffic-study-2018-13614431.php [accessed 12 July 2019].
EHang, 2020. The Future of Transportation: White Paper on Urban Air Mobility Systems. https://www.ehang.com/app/en/EHang%20White%20Paper%20on%20Urban%20Air%20Mobility%20Systems.pdf [accessed September 12, 2020].
Eker, Ugur, Ahmed, Sheikh Shahriar, Fountas, Grigorios, Anastasopoulos, Panagiotis Ch., 2019. An exploratory investigation of public perceptions towards safety and security from the future use of flying cars in the United States. Anal. Methods Accid. Res. 23, 100103. https://doi.org/10.1016/j.amar.2019.100103.
Eker, Ugur, Fountas, Grigorios, Anastasopoulos, Panagiotis Ch., 2020. An exploratory empirical analysis of willingness to pay for and use flying cars. Aerosp. Sci. Technol. 104, 105993. https://doi.org/10.1016/j.ast.2020.105993.
Eker, U., Fountas, G., Anastasopoulos, P.C., Still, S.E., 2020. An exploratory investigation of public perceptions towards key benefits and concerns from the future use of flying cars. Travel Behav. Soc. 19, 54–66. https://doi.org/10.1016/j.tbs.2019.07.003.
Fu, M., Rothfeld, R., Antoniou, C., 2019. Exploring preferences for transportation modes in an urban air mobility environment: Munich case study. Transport. Res. Rec. 2673(10), 427–442, https://doi.org/10.1177%2F0361198119843858.
'Global Summary of the Year' (2007-2017) records from Climate Data Online (NCDC) https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00947.
Greene, W.H., Hensher, D.A., 2007. Heteroscedastic control for random coefficients and error components in mixed logit. Transport. Res. E: Logist. Transport. Rev. 43 (5), 610–623. https://doi.org/10.1016/j.tre.2006.02.001.
Hawkins, A.J., 2017. Watch this all-electric 'flying car' take its first test flight in Germany. The Verge. https://www.theverge.com/2017/4/20/15369850/lilium-jet-flying-car-first-flight-vtol-aviation-munich [accessed June 1, 2018].
Hole, Arne Risa, 2007. Fitting mixed logit models by using maximum simulated likelihood. The Stata J. 7 (3), 388–401.
Larranaga, A.M., Arellana, J., Senna, L.A., 2017. Encouraging intermodality: a stated preference analysis of freight mode choice in Rio Grande do Sul. Transport. Res. Part A: Pol. Pract. 102, 202–211. https://doi.org/10.1016/j.tra.2016.10.028.
Li, Weibo, Kamargianni, Maria, 2018. Providing quantified evidence to policymakers for promoting bike-sharing in heavily air-polluted cities: A mode choice model and policy simulation for Taiyuan-China. Transport. Res. A: Pol. Pract. 111, 277–291. https://doi.org/10.1016/j.tra.2018.01.019.
Li, Z.C., Sheng, D., 2016. Forecasting passenger travel demand for air and high-speed rail integration service: a case study of Beijing-Guangzhou corridor, China. Transport. Res. A: Pol. Pract. 94, 397–410. https://doi.org/10.1016/j.tra.2016.10.002.
McFadden, D., 1974. Conditional Logit Model for Qualitative Choice Behavior. In: Zarembka, P. (Ed.), Frontiers In Econometrics. Academic Press, New York, pp. 105–142.
Miller, 2015. https://www.wired.com/2015/08/pretty-maps-bay-area-hellish-commutes/ [accessed October 2019].
Munster, Gene, 2017. Here's When Having a Self-Driving Car Will Be a Normal Thing. Fortune. http://fortune.com/2017/09/13/gm-cruise-self-driving-driverless-autonomous-cars/ [accessed May 4, 2018].
Open Street Routing Machine (OSRM), http://project-osrm.org/ [accessed November 1, 2019].
Open Trip Planner (OTP), https://www.opentripplanner.org/ [accessed November 1, 2019].
OpenStreetMap Database: https://wiki.openstreetmap.org/wiki/Downloading_data.
Parkwhiz, January 7, 2019: https://www.parkwhiz.com/.
Reeves, 2018. A dozen ways to be middle class. https://www.brookings.edu/interactives/a-dozen-ways-to-be-middle-class/ [accessed July 15, 2019].
Urban Mobility Report 2018, TTI https://mobility.tamu.edu/umr/.
SF Bay Transit, https://sfbaytransit.org/fares [accessed October 12, 2018].
Syed, N., Rye, M., Ade, M., Trani, A., Hinze, N., Swingle, H., Smith, J., Dollyhigh, S., Marien, T., 2017. Preliminary considerations for ODM Air Traffic Management based on Analysis of Commuter Passenger Demand and Travel Patterns for the Silicon Valley Region of California. In: 17th AIAA Aviation Technology, Integration, and Operations Conference (p. 3082), https://doi.org/10.2514/6.2017-3082.
Traffic Congestion and Reliability: Linking Solutions to Problems. https://ops.fhwa.dot.gov/congestion_report_04/appendix_C.htm.
Train, K.E., 2009. Discrete choice methods with simulation. Cambridge University Press.
"Transportation Secure Data Center., 2019. National Renewable Energy Laboratory. Accessed Jan. 15, 2019: www.nrel.gov/tsdc.
U.S. Census Bureau; American Community Survey, 2017 American Community Survey 5-Year Estimates, Table B19013; using American FactFinder; [accessed December 7, 2018].
U.S.Census Bureau, Center for Economic Studies, https://onthemap.ces.census.gov/ [accessed December 7, 2018].
Uber, 2016. Fast-Forwarding to a Future of On-Demand Urban Air Transportation. https://www.uber.com/elevate.pdf [accessed June 1, 2018].
Uber, 2018. Seeking an International Launch City. https://www.uber.com/info/elevate/ [accessed June 1, 2018].
Vital Signs. How much are Bay Area households making each year? http://www.vitalsigns.mtc.ca.gov/income [accessed 2 December 2019].
Washington, S., Karlaftis, M.G., Mannering, F., Anastasopoulos, P., 2020. Statistical and Econometric Methods for Transportation Data Analysis. CRC Press.

Whittle, R., 2017. Soon you'll be able to go to work in a flying taxi. New York Post. https://nypost.com/2017/04/01/soon-youll-be-able-to-go-to-work-in-a-flying-taxi/ [accessed June 1, 2018].
Winter, Scott R., Rice, Stephen, Lamb, Tracy L., 2020. A prediction model of Consumer's willingness to fly in autonomous air taxis. J. Air Transport Manage. 89, 101926. https://doi.org/10.1016/j.jairtraman.2020.101926.
Wirtz, M., Vortisch, P., Chlond, B., 2015. Flat rate bias in public transportation-magnitude and reasoning. In: 94th Annual Meeting of the Transportation Research Board, Washington, DC, January.