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Forecasting market opportunities for urban and regional air mobility

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A B S T R A C T

Analysts predict that future air taxis will fundamentally change the travel behavior of society. However, current market forecasts for air taxi demand varies widely because of inconsistencies in assumptions about travel purpose, technology acceptance, time savings, affordability, and safety. To successfully deploy Advanced Air Mobility (AAM), stakeholders need to reliably forecast routes where demand will be highest. To increase reliability, this study focuses on the Uber Elevate multimodal use case and combines top-down and bottom-up methodologies to forecast demand. The hybrid methodology forecasts demand within four distance bands from 100 miles to 400 miles, in 100-mile increments. Forecasting within distance bands informs a range roadmap for electrified vertical takeoff and landing (eVTOL) aircraft. Geographic information system (GIS) and network trimming techniques identify 2083 viable routes among 859 U.S. cities. The findings are that approximately 78,000 passengers daily will access at most 4214 vertipads to fly on 3023 four-passenger eVTOL aircraft. Serving routes within the first 100-mile band will require two and five times more capital for aircraft and vertiports, respectively, than for longer routes. AAM stakeholders can utilize the hybrid methodology to forecast demand for specific routes in other regions of the world and for additional use cases.

1. Introduction

Advanced air mobility (AAM) is a sustainable aviation initiative to connect cities across urban and regional areas with air taxis in the form of electrified vertical takeoff and landing (eVTOL) aircraft (GAO, 2022). eVTOL aircraft characteristics are favorable for operation in densely populated places because they can take off and land like helicopters in small spaces called vertipads. Unlike airports, vertipads distributed throughout a city will be closer to the origins and destinations of passengers (Ackerman et al., 2022). eVTOL aircraft promise shorter journeys, lower fares, lower traffic noise, and less pollution (NASA, 2021). Urban vertiports can spur new shuttle services between regional locations, resulting in less ground traffic. Each vertipad services a single aircraft, and each vertiport can contain multiple vertipads. In summary, motivations for AAM deployments are to increase accessibility, reduce trip times, lower fares, lower traffic noise, reduce pollution, and reduce ground traffic.

Uber Elevate described a detailed vision for the passenger AAM use case (Uber Elevate, 2016). The vision was that passengers could book complete door-to-door journeys that combine ground and air passenger modes for faster, more accessible, and more affordable transportation across longer distances. Some of the proposed locations for vertiports were at underutilized small airports and heliports, the rooftops of parking garages and shopping malls, floating barges, roadside facilities, and in the cloverleaf areas of highway exchanges (Uber Elevate, 2016). Joby Aviation acquired Uber Elevate in 2020 to commercialize the use case (Joby Aviation, Inc., 2021). The Uber Elevate business model has since attracted hundreds of eVTOL aircraft manufacturers and billions of dollars to deploy AAM (Dempsey, 2021).

Initial deployments that fail to produce a reasonable return on investment can stall AAM development. Hence, the problem to solve is where to develop routes that will serve the greatest initial demand. There is no data on existing demand locations because a commercial air taxi market does not exist at the time of this study. It is also likely that adding lower-cost air taxi services to existing regional routes will induce demand and mode shift from larger aircraft. There has been no study to rank all U.S. cities and routes by their air taxi demand potential. Therefore, the goal of this research was to rank potential U.S. routes based on the Uber Elevate business model, within the range constraints of an AAM technology roadmap.

Air passenger demand forecasting typically takes a top-down approach by considering how socioeconomic factors may influence travel demand (Suryani et al., 2010). Current market size estimates for AAM vary widely because of the inconsistencies of study scope, varying assumptions about socioeconomic factors, and guesses about deployment constraints (Sun et al., 2021). The contribution of this study is a

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hybrid methodology that ranked specific U.S. routes by trip-miles, within distance bands to inform an eVTOL aircraft range roadmap. The hybrid methodology combined top-down and bottom-up approaches. The top-down aspect was based on population projections for 2030 and trip rates based on statistics from transportation network company (TNC) operations. The year 2030 is when most air taxi companies expect to deploy commercial service (Carter et al., 2022). The bottom-up aspect of the methodology identified potential air taxi routes by using a geographic information system (GIS) to produce a Haversine distance matrix among all pairwise combinations of cities selected. The results of this study will inform investment decisions, transportation planning, standardization initiatives, regulatory developments, and policymaking.

The organization of the rest of this paper is as follows: Section 2 reviews the literature on AAM market forecasts, air travel demand modeling, TNC statistics, and bottom-up studies. Section 3 describes the hybrid methodology introduced to forecast and rank specific U.S. routes based on their trip-mile potential. Section 4 discusses the results and implications for AAM stakeholders. Section 5 concludes the research and hints at future work already underway.

2. Literature review

Ghalehkhondabi et al. (2019) suggested that there is no single method of forecasting air passenger demand that works best for all scenarios (Ghalehkhondabi et al., 2019). Current demand forecasts vary widely because of the variety of assumptions made and the range of scenarios investigated. For instance, Porsche Consulting estimated that the global passenger market for AAM in 2035 will be $32 billion (Grandl et al., 2018). In contrast, Morgan Stanley Research estimated that the same market in 2035 will be $641 million (Morgan Stanley Research, 2019). Lineberger et al. (2021) estimated that the U.S. AAM market alone will be $115 billion by 2035 (Lineberger et al., 2021). A literature review by Banerjee et al. (2020) suggested that standardizing forecasting methods will improve consistency (Banerjee et al., 2020). The U. S. National Academies of Science (NAS) validated a need for more research in AAM forecasting by launching a synthesis study in 2021 to further compare existing methods and assumptions (Fowler, 2021).

Classic travel demand forecasting begins by estimating future trip production rates based on surveys or assumptions about how often people will travel for different purposes such as work, shopping, leisure, school, and to access services (Bridgelall and Stubbing, 2021). However, the dynamics of remote work policies and e-commerce introduce additional uncertainty. Although anticipated to grow rapidly, many issues can delay AAM adoption such as concerns about community acceptance (Kalakou et al., 2023), lack of supporting infrastructure for smart city integration (Richter et al., 2020), and environmental impacts (Cohen et al., 2021). Other concerns include safety, security, operational robustness in all weather conditions, visual and noise pollution, aircraft technology limitations, inequitable accessibility, and service unaffordability (Garrow et al., 2021). Top-down methods typically assume estimates for population, gross domestic product, price, need, and service quality (Suryani et al., 2010). Forecasters also apply macroeconomic indicators to linear models (Njegovan, 2005), and time-series models with seasonality (Jungmittag, 2016).

Statistics from specific use cases help to decrease uncertainty. For instance, a Gallup poll found that 30 % of Americans used ridesharing, which ties demand for the Uber Elevate use case directly to population (Reinhart, 2018). A few studies examined the potential for AAM to capture some of the ground TNC market. Rothfeld et al. (2018) found that ground trips longer than 10 km (6 miles) could compete with an air taxi market (Rothfeld et al., 2018). Another study found that air taxi trips need to be longer than 15 to 25 km (9 to 16 miles) to entice a mode shift for more time savings (Baur et al., 2018). Goyal et al. (2021) found that AAM could capture 98 % of ground trips longer than 30 min and replace non-discretionary car trips that take >45 min (Goyal et al., 2021). The Goyal study focused on ten metropolitan regions in the United States and estimated a constrained daily demand of 82,000 passengers served by 4100 four- or five-seat aircraft. Kooti et al. (2017) analyzed >4 million Uber trip receipts and found that more than half the rides were shorter than four miles and 10 % were longer than 36 min (Kooti et al., 2017). The Kooti study also found that the median trip duration was 14 min, and the median trip rate was 10.4 rides per year. Wang et al. (2022) analyzed street images of Atlanta, Georgia, and found that the average wait time for an UberX ride was approximately 6 min (Wang et al., 2022).

Very few research tackled forecasting by bottom-up approaches that consider specific routes. Bottom-up methods are more challenging because they require additional granularity and computational resources to evaluate details about the origin and destination characteristics for the considered routes. Rakas et al. (2021) used multi-criteria decision analysis to rank the suitability of eVTOL aircraft designs for specific routes across the Los Angeles, California, metropolitan area (Rakas et al., 2021). A U.K. study found that conventional regional aircraft used only 11 % of their range capability to serve sector lengths up to 1000 km (Swanson and Zych, 2022). The U.K. study suggested that electric aircraft with range capability up to 500 km (311 miles) can more efficiently serve a majority of that sector. In summary, there has been no AAM forecasting method that combined top-down and bottom-up approaches.

3. Methodology

A NASA-commissioned study found that 98 % of the air taxi demand will come from a portion of ground trips that exceed 30 min (Goyal et al., 2019). Therefore, this study focused on the Uber Elevate use case, which could be the largest initial market for air taxis. The Uber Elevate scenario generates air taxi demand by shifting modes from ground to air for a portion of the TNC ride journey. The analyzed scenario assumes that there is no lack of supply in the horizon year that would influence demand. The next six subsections discuss the data mining workflow, the variables and values used in the calculations, and the methods of trip generation, network trimming, trip distribution, and supply-side estimates.

3.1. Data mining workflow

Fig. 1 illustrates the data mining and analytical workflow where each procedure shown is a function implemented in the Python programming language. The workflow starts with 2010 and 2020 population estimates from the United States Census Bureau (USCB) for all incorporated U.S. cities (USCB, 2022). The model to forecast population for each city in 2030 was a linear projection based on population changes from 2010 to 2020. The linear projection captured a decade-long change in population for each city as a nominal slope and projected the same change to the next decade.

Estimates for the trips generated and the mode shift propensity for each city were based on TNC statistics reported by the Gallup poll (Reinhart, 2018) and the Kooti et al. (2017) analysis of more than four million Uber trip receipts (Kooti et al., 2017). The network trimming procedures removed nodes and links that would be unattractive for AAM deployments based on low departure rates.

Route length classification binned all potential routes between the selected cities within distance bands of 100 miles to 400 miles, in 100-mile increments. The four distance bands align with four stages of a proposed eVTOL technology roadmap to increase operating range. That is, steady advancements in battery energy density, lightweight airframe material, propulsion system efficiency, and automation will increase eVTOL aircraft range (Lee et al., 2020). Forecasting demand within distance bands will help AAM stakeholders make decisions about reaching additional markets served by longer routes.

The advantage of ranking routes based on their *relative* trip-mile

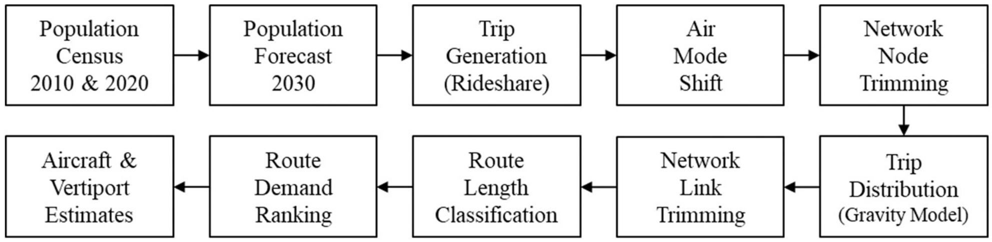

Fig. 1. The data mining and analytical workflow of this study.

potential was that ranking is insensitive to estimate variations for trip rate and mode shift. Hence, using rank instead of an absolute demand rate identifies important routes for prioritized development based on their relative business potential. For example, the absolute size of the potential market within a top ten list of routes would depend on the actual mode shift from ground TNC rides, but those routes will remain on the top ten list.

3.2. Scenarios and variables

Table 1 summarizes the variables (Vars) used in the analysis and includes their value, units, and data source. Uber Elevate suggested that a four-passenger aircraft will achieve the AAM vision better than larger aircraft because of the strict community noise restrictions (Uber Elevate, 2016). Uber Elevate calculated that 125 mph yielded the maximum motion efficiency (miles/kwh) for eVTOL aircraft in cruise mode (Uber Elevate, 2016). This speed is coincidentally the same as the average speed specification for eVTOL aircraft under development (Bridgelall et al., 2023). Therefore, this analysis used 125 mph as the average eVTOL aircraft cruise speed.

The average range specification for eVTOL aircraft under development was 91 miles (Bridgelall et al., 2023). Although a few manufacturers demonstrated full-size prototype flights, the robust range capability of eVTOL aircraft under real-world scenarios like inclement weather, temperature extremes, and wind gusts, was unverified at the time of this research (Nickels, 2021). However, most manufacturers that announced plans to launch service by 2030 were designing aircraft to serve routes within 100-miles, including a buffer distance to comply with regulatory safety requirements (FAA, 2020). Manufacturers have also been developing hybrid VTOL aircraft that can service routes of up to 400 miles (Rakas et al., 2021).

The battery charge time of 30 min reflected current developments in fast chargers that would be suitable for the AAM market (Rajendran et al., 2021). Battery swapping could potentially reduce the aircraft ground time, thereby increasing utilization. However, battery swapping may require additional personnel, which would increase operating costs and the need for training and safety inspections. Therefore, this analysis calculates the departure capacity of a vertipad based on aircraft occupation time, which is the total time required to descend, charge, and liftoff. The scenario was that the total time required for disembarking, cleaning, and boarding will be comparable to the charge time.

The operating scenario was that the first and last departure times would be 6 a.m. and 8 p.m., respectively. The rationale was to operate during the average summer daylight time in the continental United States (WorldData.info, 2023). Therefore, the capacity of a vertipad under the above scenarios was

$$V_c = \left\lceil \frac{60 H_O}{B_c + T_L + T_D} \right\rceil = 26 \tag{1}$$

where ⌈ • ⌉ is the mathematical ceiling function that rounds up a value to the nearest integer. This equation reflects an ideal capacity that does not include any additional time for potential “safety intervals” that a future air traffic management system might require.

Table 1
Data used in the analysis.

Vars	Description	Value	Units	Source
D_m	Average eVTOL flight range advertised	91	Miles	(Bridgelall, Askarzadeh, & Tolliver, Introducing an Efficiency Index to Evaluate eVTOL Designs, 2023)
B_N	Distance band category	{100, 200, 300, 400}	Miles	
S_m	Average eVTOL cruise speed advertised	125	MPH	(Bridgelall, Askarzadeh, & Tolliver, Introducing an Efficiency Index to Evaluate eVTOL Designs, 2023)
S_e	Cruise speed for peak motion efficiency	125	MPH	(Uber Elevate, 2016)
B_c	Aircraft battery charge time	30	Minutes	(Rajendran et al., 2021)
T_L	Aircraft vertical lift time	1	Minute	(Uber Elevate, 2016)
T_D	Aircraft vertical descent time	1	Minute	(Uber Elevate, 2016)
H_O	Operating Hours (6 a.m. to 8 p.m.)	14	Hours	(WorldData.info, 2023)
D_C	Drone passenger capacity +1 pilot	4	Count	(Uber Elevate, 2016)
P_i	2030 population estimate for city at node *i*	Var	Count	(USCB, 2022)
XY_i	Centroid geospatial coordinates for node *i*	Var	degrees	(SimpleMaps, 2020)
r_p	Proportion of population using TNC rides	0.30	Proportion	(Reinhart, 2018)
r_r	Average annual TNC ride trip rate	10.4	per year	(Kooti et al., 2017)
r_{AP}	Proportion of Uber trips accessing airports	0.17	Proportion	(Uber Elevate, 2016)
r_{36}	Proportion of rides longer than 36 min	0.10	Proportion	(Kooti et al., 2017)
r_{60}	Proportion of rides longer than 60 min	0.06	Proportion	(Uber Elevate, 2016)
R_T	Average TNC ride trip time	14	Minutes	(Kooti et al., 2017)
R_W	Average TNC ride wait time	5.8	Minutes	(Wang et al., 2022)
H_D	Haversine distance factor of road distance	0.71	Proportion	(Uber Elevate, 2016)

3.3. Trip generation

Uber found that <17 % of all its bookings connected to airports (Uber Elevate, 2016). However, data is not available about the portion of those bookings that involved urban or regional air travel within 400 miles. A related data point is that regional airlines accounted for 41 % of all scheduled U.S. passenger flights in 2021 (RAM, 2023). Hence, an informed estimate for the Uber Elevate use case was that 17 % x 41 % = 7 % of bookings would be for regional flights, but of unknown distance. Another data point from Kooti et al. (2017) was that 10 % of TNC trips were longer than 36 min (Kooti et al., 2017). Uber Elevate reported that 6 % of TNC trips were longer than 60 min (Uber Elevate, 2016). Hence, the above datapoints support a plausible scenario that between 6 % and 10 % of TNC users will switch to air taxis that will reduce overall travel time to below 36 min.

That is, the value 3.21 = 1/(0.3 × 10.4 × 0.10). Therefore, the annual number of four-passenger drone departures from node *i* is

$$\mathrm{A_i} = \frac{\mathrm{Y_i}}{\mathrm{D_C}} = \frac{\mathrm{P_i}}{3.21 \times 4} = \frac{\mathrm{P_i}}{12.82} \tag{3}$$

Hence, the average number of *daily* four-passenger drone departures from node *i* is

$$\mathrm{D_i} = \frac{\mathrm{A_i}}{365} = \frac{\mathrm{P_i}}{4679.5} \tag{4}$$

Table 2 summarizes the variables used in the calculations. Given that 30 % of the population uses TNC and that the average annual trip rate is 10.4 (Table 1), the estimated average annual passenger departures from all vertiports at node *i* is

$$\mathrm{Y_i} = \mathrm{P_i r_p r_r r_{36}} = \frac{\mathrm{P_i}}{3.21} \tag{2}$$

That is, the value 3.21 = 1/(0.3 × 10.4 × 0.10). Therefore, the annual number of four-passenger drone departures from node *i* is

$$\mathrm{A_i} = \frac{\mathrm{Y_i}}{\mathrm{D_C}} = \frac{\mathrm{P_i}}{3.21 \times 4} = \frac{\mathrm{P_i}}{12.82} \tag{3}$$

Hence, the average number of *daily* four-passenger drone departures from node *i* is

$$\mathrm{D_i} = \frac{\mathrm{A_i}}{365} = \frac{\mathrm{P_i}}{4679.5} \tag{4}$$

The above quantity is equivalent to 0.021 % of the population at a node. For perspective, the above model predicts that a city of 9359 persons will have 2808 TNC users (30 %) who would produce an average demand of two daily four-passenger drone departures.

Table 2
Variables used in the analysis.

Vars	Description	Units
Y_i	Average annual passenger departures from node *i*	Count
A_i	Average annual drone departures from node *i*	Count
$D\{i, j\}$	Average daily drone round trips on route $\{i, j\}$	Count
M_{ij}	Average daily trip-miles between nodes *i* and *j*	Trip-Miles
d_{ij}	Haversine distance between nodes *i* and *j*	Miles
F_{ij}	Flight time between nodes *i* and *j*	Minutes
Δ_{ij}	Time between availability of the same aircraft at node *i*	Minutes
R_{ij}	Road distance between nodes *i* and *j*	Miles
G_{ij}	Ground (road) travel time between nodes *i* and *j*	Minutes
r_{ij}	Flight time to road time ratio between nodes *i* and *j*	Proportion
$N\{i, j\}$	Number of drones serving route$\{i, j\}$	Count
$Q\{i, j\}$	Average daily departures per drone on route$\{i, j\}$	Count
$U\{i, j\}$	Average annual aircraft utilization on route$\{i, j\}$	Hours
V_c	Vertipad capacity (daily departures per vertipad)	Count
$V\{i, j\}$	Vertipads needed at each trip end of route$\{i, j\}$	Count
V_i	Minimum number of vertipads needed at node *i*	Count

3.4. Network trimming

The network model to select route candidates represented cities as nodes. The value of each node was the number of daily drone departures. The value of a link between each node pair was the Haversine distance between city centers, which approximated a direct flight path. A fully connected network of N nodes has $N^2 - N$ links. The USCB population dataset contained 19,494 cities, which resulted in approximately 380 billion route candidates. The strategy to reduce the problem size for practical evaluation and planning was to trim the network in stages, based on a set of criteria.

Network trimming started with node elimination and then proceeded with link elimination. Node elimination was based on a minimum demand threshold. Link elimination was based on a Haversine distance window. Node trimming removed nodes in three stages to gauge the progressive effectiveness of each. The first stage eliminated cities where the population was insufficient to generate at least one drone departure per day. The threshold was 365 × 4 = 1460 annual person-departures, based on four-passenger drones. The second stage removed places in Alaska, Puerto Rico, and Hawaii to focus the forecast on the contiguous United States.

After applying trip generation, the third stage eliminated cities with, at most, two daily drone departures ($D_i \leq 2$). The rationale was that investors and transportation providers will deploy initial service to maximize daily revenue and aircraft utilization for the least amount of capital investment. The threshold of two daily departures reflected the scenario that a single aircraft can provide only one to two daily round trips within a 400-mile distance band.

The minimum and maximum distance for link trimming was 15 and 400 miles, respectively. The maximum distance was the upper limit of the last distance band, which was 400 miles. Setting the lower limit to 15 miles was based on the total journey time of a typical TNC trip in large U.S. cities, which was 20 min (6 min of waiting and 14 min of riding). When traveling at the typical arterial speed limit of 45 mph, a zero-wait 20-min ride will go approximately 15 miles.

Link trimming required the Haversine distances for every pairwise combination of nodes remaining on the trimmed network. A geospatial information systems (GIS) tool provided those distances by using the centroid of cities to generate a distance matrix. However, the USCB population dataset lacked geospatial coordinates for the city centroids. The solution was to merge another dataset that contained those geospatial coordinates. However, merging the two datasets required a common unique variable or key, but none existed. Therefore, the strategy was to create a unique key by concatenating the city name with the state name. It was not possible to use only city names as the merge key because of many duplicates. Finally, data cleaning was necessary to correct mismatches in the city names across datasets due to differences in prefix spellings like "St." versus "Saint" and differences in name suffixes such as "City," "village," "town," "borough," and "municipality."

3.5. Trip distribution

One of the most important models in trip distribution is the *gravity model of migration* that estimates the number of trips that would go from node *i* to node *j* based on the concept of attraction (Zhang et al., 2018). Inspired by Newton's law of gravity, the model represents "attraction" between two locations as the product of their individual *importance* and the inverse of an *impedance* factor between them. The number of daily departures based on population was the measure of importance, and the impedance factor was the squared Haversine distance between them. The basic gravity model does not account for *relative* importance among all possible routes from an origin node. Hence, the strategy was to modify the model to reflect equal weight between the relative importance and relative impedance of locations with routes connecting to node *i*. That is, let $\{J\}$ be the set of nodes $j = \{1, 2 \ldots\}$ connected to node *i*. Hence, the number of departures that node *j* attracts from node *i* is

$$D_{ij} = D_i\left[\frac{1}{2}\left(\frac{D_j}{\sum_{j\in\{J\}} D_j}\right) + \frac{1}{2}\left(\frac{1/d_j^2}{\sum_{j\in\{J\}}\left(1/d_j^2\right)}\right)\right] \bullet \tag{5}$$

Airlines use the concept of "passengers daily each way" (PDEW) to measure the demand on a regional route (Bachwich and Wittman, 2017). PDEW assumes that passengers arriving at node *i*, especially commuters and business travelers, will return at some time. Therefore, returning passengers at node *i* will add to its departing passengers. Hence, the number of *round trips* on route {*i*, *j*} was the sum of departures originated at each trip end such that

$$D\{i,j\} = \lfloor D_{ij} + D_{ji} \rfloor \tag{6}$$

where the operator $\lfloor \bullet \rfloor$ is the mathematical floor function that rounds down a value to the nearest integer.

3.6. Supply estimates

The flight time from node *i* to node *j* is

$$F_{ij} = \frac{D_m}{S_m} + T_L + T_D \bullet \tag{7}$$

Based on round trips, the time between availability of the same aircraft at node *i* is

$$\Delta_{ij} = 2\left(B_c + F_{ij}\right) \bullet \tag{8}$$

The number of four-passenger drones needed to serve route {*i*, *j*} is

$$N\{i,j\} = \left\lceil \frac{D\{i,j\}\Delta_{ij}}{60 H_O} \right\rceil \bullet \tag{9}$$

The average number of daily one-way trips per drone that serve route {*i*, *j*} is

$$Q\{i,j\} = \left\lceil \frac{2 \times D\{i,j\}}{N[i,j]} \right\rceil \bullet \tag{10}$$

The average daily trip-miles for route {*i*, *j*} is

$$M_{ij} = 2 \times D\{i,j\} F_{ij} \tag{11}$$

The average aircraft utilization on route {*i*, *j*} in annual flight hours is

$$U\{i,j\} = Q\{i,j\} \times F_{ij} \times 365/60 \bullet \tag{12}$$

The number of vertipads needed at each trip end of route {*i*, *j*} is

$$V\{i,j\} = \left\lceil \frac{D\{i,j\}}{V_c} \right\rceil \tag{13}$$

Vertipads dedicated for specific routes may be underutilized. Hence, sharing a vertipad to serve multiple routes will increase utilization. Therefore, the lower bound for the number of route-shared vertipads needed at node *i* is

$$V_i = \left\lceil \frac{\sum_{j\in\{J\}} D\{i,j\}}{V_c} \right\rceil \tag{14}$$

The lower bound represents the theoretical scenario of 100 % vertipad capacity utilization. Practically, however, more vertipads will be necessary to design some slack in the system that would accommodate operational variations such as flight, departure, and charge times.

4. Results and discussion

The first two subsections that follow discuss results of the network trimming and demand forecasting. The last two subsections discuss the potential travel time savings over ground transportation and limitations of the study.

4.1. Network trimming

The first procedure in the workflow was to clean the population datasets to enable their merging to forecast the 2030 population for each city. The USCB dataset contained 81,415 entries but only 19,494 were incorporated U.S. cities, identified by the field value SUMLEV = 162. The number of cities decreased to 19,444 after removing duplicates. Eliminating cities where the population was insufficient to generate at least one drone departure per day reduced the number of candidate cities by 56 % to 8561. Removing locations in Alaska, Puerto Rico, and Hawaii resulted in a slight reduction to 8525 cities. Subsequently, eliminating cities with daily drone departures of at most two ($D_i \le 2$) reduced the candidate cities by a further 60 % to 3434.

After data cleaning and merging the 2030 population forecast with the geospatial coordinate dataset, the GIS produced a distance matrix with 11,788,922 (3434^2–3434) candidate routes. Trimming link distances to at most 400 miles reduced the number of candidate routes by 83.7 % to 1,920,076 routes. Trimming link distances to at least 15 miles further reduced the number of candidate routes by another 2 % to 1,884,764 routes.

The modified gravity model distributed trips from each of the remaining origin cities to all destination cities within the (15 ≤ miles ≤400) distance window. Then eliminating routes with fewer than two daily departures reduced the number of routes to 4166, which was a factor of >452. Given that each end of each route had the same number of departures and the same flight distance, the final procedure combined their individual unidirectional links to bidirectional links for faster processing. The final trimmed network consisted of 859 cities connected by 4166/2 = 2083 unique routes.

4.2. Demand forecasting

Table 3, Table 4, Table 5, and Table 6 list the top ten routes within the 100-, 200-, 300-, and 400-mile distance bands, respectively. The tables rank the routes by average daily trip-miles. Routes that service cities in New York, Texas, and California consistently ranked highest by trip-miles in each of the four distance bands. Table 3 revealed that serving the top ten routes within the 100-miles band will require an average of 4.4 drones per city for a total of 44 drones. The average route distance in the 100-mile band was 77 miles with aircraft producing an average of 3731 daily trip-miles. The {New York City ↔ Philadelphia} route will require 22 drones that will produce more than five times the average daily trip miles in the top ten routes of the 100-miles band. New York City will require at least 95 vertipads when shared across all routes to maximize utilization. The {New York City ↔ Philadelphia} route alone will require five of those 95 vertipads.

Table 7 summarizes the results for the top ten routes across all distance bands. Once again, the largest cities in California, New York, and Texas ranked highest in trip-miles. The above findings align with intuitive expectations that air taxi demand will be highest in the most populated U.S. cities. Table 8 summarizes the results for all 2083 routes within each distance band. The "Departures" column lists the total daily one-way drone departures on all routes within the indicated distance band. That is, the forecast was 19,424 daily drone departures carrying 19,424 × 4 = 77,696 passengers across all 2083 routes. The "Drones" column of Table 8 shows that 3023 four-passenger drones can serve all 2083 routes each day. The "Trip-Miles (K)" column of Table 8 lists the number of daily trip-miles (in thousands) that drones would produce within each indicated distance band. The "Vertipads" column lists the total number of vertipads needed to serve routes within the distance band indicated. That is, companies will need to build at most 4214 vertipads to service all 2083 routes each day. However, vertipads will be underutilized if reserved to service only a given route. Therefore, using the same vertipad to schedule departure slots for multiple routes will minimize the number of vertipads needed. The lower bound was 1269, which is the sum of vertipads based on the total departures in each of the

Table 3
Metrics for the Top Ten 100-mile Rand Routes.

Top Ten (100-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j
New York_NY ↔ Philadelphia_PA	20,665	79	40.2	94	110	0.370	130	22	12	2931	5	95	11
Austin_TX ↔ San Antonio_TX	3107	74	37.5	80	77	0.490	21	4	11	2510	1	10	14
Los Angeles_CA ↔ Bakersfield_CA	2037	93	46.4	111	113	0.410	11	3	8	2260	1	42	2
Denver_CO ↔ Colorado Springs_CO	1985	62	31.8	71	68	0.470	16	3	11	2126	1	7	4
New York_NY ↔ Hartford_CT	1769	98	49.2	116	146	0.340	9	2	9	2692	1	95	1
New York_NY ↔ Allentown_PA	1636	82	41.3	93	106	0.390	10	2	10	2510	1	95	1
New Haven_CT ↔ New York_NY	1618	67	34.4	80	115	0.300	12	2	12	2509	1	1	95
Chicago_IL ↔ Milwaukee_WI	1546	86	43.2	92	89	0.490	9	2	9	2366	1	16	1
Waterbury_CT ↔ New York_NY	1511	76	38.3	95	121	0.320	10	2	10	2327	1	1	95
New York_NY ↔ Bridgeport_CT	1437	51	26.6	65	101	0.260	14	2	14	2269	1	95	1
Average	3731	77	38.9	90	105	0.384	24.2	4.4	10.6	2450	1.4	45.7	22.3

Table 4
Metrics for the top ten 200-mile band routes.

Top Ten (200-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j
New York_NY ↔ Boston_MA	24,434	185	90.9	215	234	0.390	66	19	7	3869	3	95	5
San Antonio_TX ↔ Houston_TX	15,958	190	93.2	198	183	0.510	42	13	7	3968	2	14	25
Baltimore_MD ↔ New York_NY	12,033	172	84.5	188	203	0.420	35	10	7	3599	2	2	95
Austin_TX ↔ Houston_TX	9053	146	72.1	165	156	0.460	31	8	8	3508	2	10	25
San Diego_CA ↔ Los Angeles_CA	8771	115	57.4	120	135	0.430	38	8	10	3492	2	10	42
New York_NY ↔ Worcester_MA	6493	155	76.2	176	195	0.390	21	6	7	3245	1	95	1
Austin_TX ↔ Dallas_TX	5803	181	89.0	195	173	0.510	16	5	7	3792	1	10	12
Portland_OR ↔ Seattle_WA	5791	145	71.5	174	166	0.430	20	5	8	3479	1	5	7
Los Angeles_CA ↔ Fresno_CA	5598	200	98.0	220	214	0.460	14	5	6	3576	1	42	3
Indianapolis_IN ↔ Chicago_IL	5233	164	80.5	183	178	0.450	16	5	7	3427	1	4	16
Average	9917	165	81.3	183	184	0.445	29.9	8.4	7.4	3596	1.6	28.7	23.1

Table 5
Metrics for the top ten 300-mile band routes.

Top Ten (300-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j
New York_NY ↔ Washington_DC	24,269	206	100.7	226	255	0.390	59	19	7	4289	3	95	5
Los Angeles_CA ↔ San Jose_CA	15,808	293	142.5	341	329	0.430	27	12	5	4335	2	42	6
Dallas_TX ↔ Houston_TX	15,586	223	108.9	239	215	0.510	35	12	6	3974	2	12	25
Houston_TX ↔ Fort Worth_TX	13,728	237	115.6	262	233	0.500	29	11	6	4220	2	25	9
New York_NY ↔ Buffalo_NY	13,040	296	144.3	375	383	0.380	22	10	5	4388	1	95	1
San Diego_CA ↔ Phoenix_AZ	11,840	296	144.1	355	329	0.440	20	9	5	4382	1	10	17
Chesapeake_VA ↔ New York_NY	11,819	269	130.9	368	401	0.330	22	9	5	3983	1	2	95
San Antonio_TX ↔ Dallas_TX	11,086	252	122.9	274	263	0.470	22	9	5	3739	1	14	12
New York_NY ↔ Richmond_VA	10,203	269	130.9	340	388	0.340	19	8	5	3981	1	95	1
Norfolk_VA ↔ New York_NY	9887	291	141.6	363	395	0.360	17	7	5	4306	1	1	95
Average	13,727	263	128.2	314	319	0.415	27.2	10.6	5.4	4160	1.5	39.1	26.6

Table 6
Metrics for the top ten 400-mile band routes.

Top Ten (400-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j
Phoenix_AZ ↔ Los Angeles_CA	36,518	365	177.3	372	352	0.500	50	25	4	4314	2	17	42
New York_NY ↔ Virginia_VA	26,518	390	189.2	388	454	0.420	34	18	4	4604	2	95	2
San Francisco_CA ↔ Los Angeles_CA	16,901	338	164.3	383	365	0.450	25	12	5	4996	1	5	42
El Paso_TX ↔ Phoenix_AZ	14,717	350	170.2	430	387	0.440	21	11	4	4141	1	6	17
Mesa_AZ ↔ Los Angeles_CA	12,420	388	188.3	389	373	0.500	16	9	4	4582	1	5	42
Pittsburgh_PA ↔ New York_NY	12,116	319	155.1	388	372	0.420	19	9	5	4716	1	1	95
Nashville_TN ↔ Chicago_IL	11,028	394	191.1	442	462	0.410	14	8	4	4649	1	4	16
Sacramento_CA ↔ Los Angeles_CA	10,540	351	170.6	386	367	0.460	15	8	4	4152	1	2	42
Houston_TX ↔ New Orleans_LA	9843	328	159.5	348	326	0.490	15	7	5	4851	1	25	2
New York_NY ↔ Akron_OH	8769	399	193.3	438	427	0.450	11	6	4	4704	1	95	1
Average	15,937	362	175.9	396	389	0.454	22	11.3	4.3	4571	1.2	25.5	30.1

859 cities. Hence, optimizing departure slots to maximize vertipad utilization could reduce the number of vertipads needed by a factor of $4214/1269 = 3.3$. Future work will conduct a few case studies to optimize vertipad utilization and location within cities.

Fig. 2 plots the data in Table 8 to visualize the forecasted demand trend across distance bands. Fig. 2a shows opposing trends in the number of one-way departures and trip-miles.

The number of one-way departures decreased by a factor of 5.9 after the first 100-mile band and then remained steady. The trip-miles changed only slightly from the 100- to the 200-mile band but more than doubled within the 400-mile band. This result suggests that targeting services in a higher distance band will increase revenue if based on seat-miles. On the other hand, starting service in the first 100-mile band will capture a greater portion of the market in terms of

Table 7
Metrics for the top ten routes among all distance bands.

Top ten (overall)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j	B_N
Phoenix_AZ ↔ Los Angeles_CA	36,518	365	177.3	372	352	0.500	50	25	4	4314	2	17	42	400
New York_NY ↔ Virginia_VA	26,518	390	189.2	388	454	0.420	34	18	4	4604	2	95	2	400
New York_NY ↔ Boston_MA	24,434	185	90.9	215	238	0.380	66	19	7	3869	3	95	5	200
New York_NY ↔ Washington_DC	24,269	206	100.7	226	255	0.390	59	19	7	4289	3	95	5	300
New York_NY ↔ Philadelphia_PA	20,665	79	40.2	95	106	0.380	130	22	12	2931	5	95	11	100
San Francisco_CA ↔ Los Angeles_CA	16,901	338	164.3	383	365	0.450	25	12	5	4996	1	5	42	400
San Antonio_TX ↔ Houston_TX	15,958	190	93.2	198	183	0.510	42	13	7	3968	2	14	25	200
Los Angeles_CA ↔ San Jose_CA	15,808	293	142.5	341	329	0.430	27	12	5	4335	2	42	6	300
Dallas_TX ↔ Houston_TX	15,586	223	108.9	239	215	0.510	35	12	6	3974	2	12	25	300
El Paso_TX ↔ Phoenix_AZ	14,717	350	170.2	430	386	0.440	21	11	4	4141	1	6	17	400
Average	21,137	262	127.7	289	288	0.441	48.9	16.3	6.1	4142	2.3	47.6	18.0	300

Table 8
Demand forecast summary.

Band	Routes	Departures	Trip-Miles (K)	Drones	Vertipads
100	1370	13,010	360	1547	2762
200	234	2238	359	398	480
300	205	2028	506	454	420
400	274	2148	749	624	552
Total	2083	19,424	1973	3023	4214

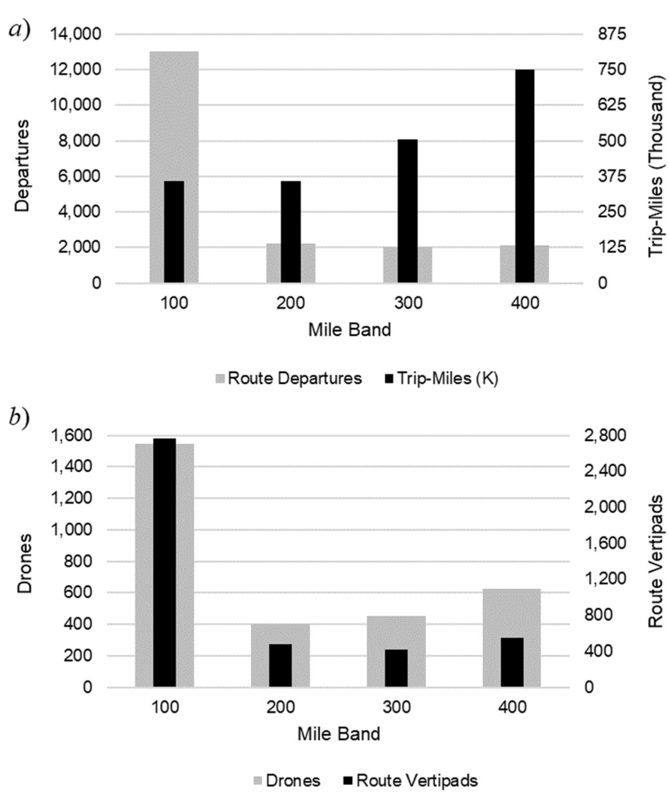

Fig. 2. Revenue factors of *a*) departures and trip-miles, and *b*) capital factors of drones and vertipads.

passenger volume, albeit at lower trip-miles. This finding suggests that a non-linear fare structure would generate more revenue by charging a higher base rate within the first 100-miles, and then by seat-mile for longer distances. Service within the first 100-mile band will require more than double the number of aircraft than serving longer routes. The number of vertipads needed on both ends of routes within the first 100-mile band was more than five times that needed for longer distances. The above findings imply that the capital required to capture initial markets serving the first 100-miles will be a factor of two and five times larger to purchase aircraft and build vertiports, respectively.

Aircraft utilization is another important consideration in the commercial aviation business (NASA, 2021). Greater aircraft utilization, measured in annual hours flown, spreads fixed costs across more revenue service hours (Pertz et al., 2023). The aircraft utilization rate increases with longer distance routes. Hence, the time spent on the ground refueling, boarding, disembarking, and cleaning becomes a smaller percentage of the daily operating hours. As summarized in Table 3, the average annual aircraft utilization for the top ten routes within the first 100 miles band was 2450 h. For comparison, the average annual utilization of small regional jets and turboprops in the United States were 2263 and 2665 h, respectively (FAA, 2022). The average aircraft utilization within the 400-mile band will increase by 86.5 % from the average utilization within the first 100-mile band.

Fig. 3 maps the cities (trip-ends) that generated at least two drone trips ($D_i \geq 2$) as small black dots and highlights the cities of the trimmed network as larger dots. For comparison, Fig. 3a and Fig. 3b maps the location of cities with routes within the 100- and 400-mile bands, respectively. The maps show that the density of cities with routes within the first 100-mile band is visibly higher than those with routes within the 400-mile band. The dense city clusters in each map align with the top ten locations summarized in Table 3, Table 4, Table 5, and Table 6.

4.3. Travel time savings

For the top ten routes within each distance band, Table 9 summarizes the mean air miles (μ AMiles), mean air minutes (μ AMin), mean road miles (μ RMiles), mean road minutes (μ RMin), mean air/road time ratio (μ A/R), and the mean person years saved daily (μ PYSD). Fig. 4 plots the data in Table 9 to visualize the trends across distance bands. The daily mean PYSD was 2.4 in the first 100-mile band and accumulated to 10.1 in the 400-mile band. For comparison, Uber Elevate estimated that in 2016, San Francisco residents lost the equivalent of 57 years of productivity daily by wasting time in road traffic (Uber Elevate, 2016). This result highlights that time savings from the Uber Elevate use case alone would be substantial.

At the average aircraft speed of 125 mph, the average travel time ratio for air/ground was approximately 38 % within the first 100-mile band and increased to 45 % within the 400-mile band. Hence, the average travel time ratio within the first 100-mile band was 7 % lower than the average across the 200-mile to 400-mile bands. That is, travel time savings by switching from cars to drones will be largest for routes within the first 100 miles. Flying at higher speeds will proportionally decrease in the travel time ratio, which could further increase the propensity for mode shift to drones. The above time-saving ratios are comparable to the 40 % reported in the Uber Elevate study (Uber Elevate, 2016).

Depending on the number of drivers available, wait-time can become a deterrent in TNC trips. By extension, AAM processing time (access, security clearance, boarding, disembarking, and egress) and aircraft speed will become crucial factors in air taxi adoption. Therefore, to spur

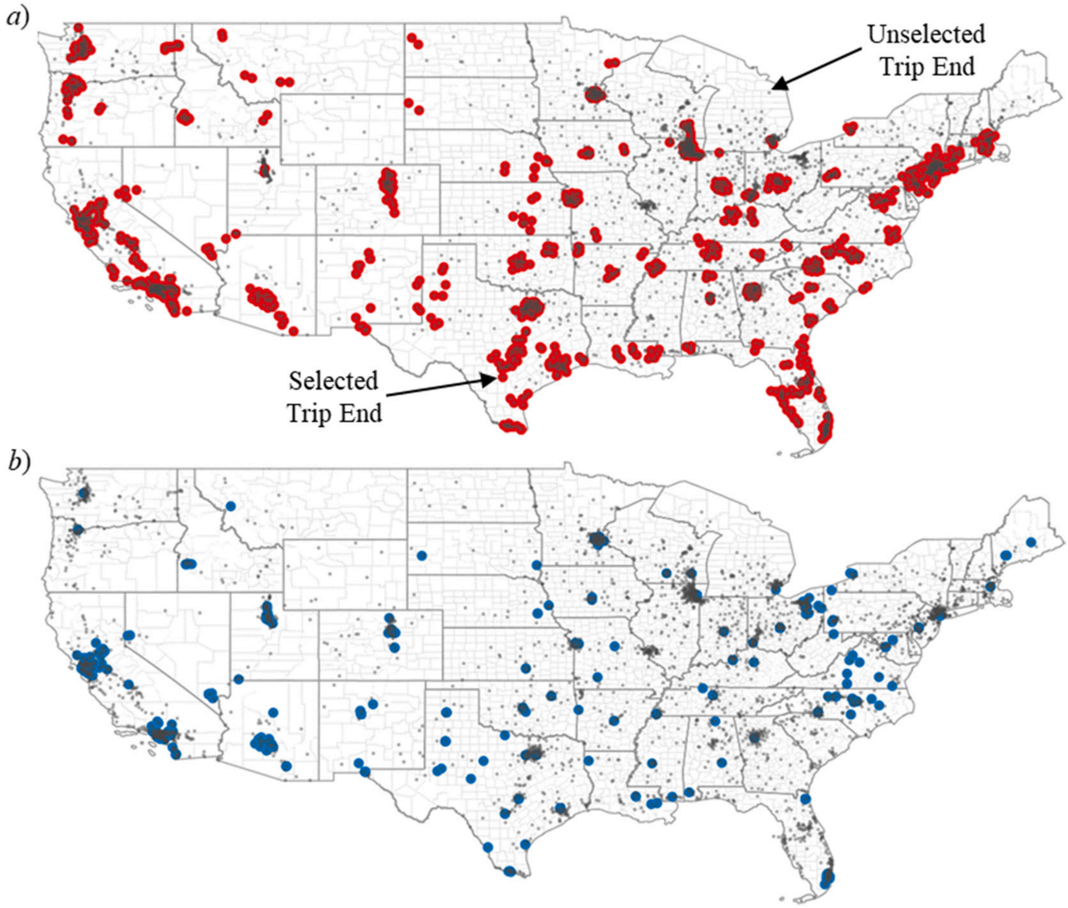

Fig. 3. Trip ends selected *a*) within a 100-mile band, and *b*) within a 400-mile band.

Table 9
Time saving statistics.

Distance band	μ AMiles	μ AMin	μ RMiles	μ RMin	μ A/R	μ PYSD
100	76.8	38.9	89.7	104.6	0.384	2.4
200	165.3	81.3	183.4	183.7	0.445	1.7
300	263.0	128.2	314.3	319.1	0.415	2.6
400	362.2	175.9	396.4	388.5	0.454	3.3

adoption, providers must strive to minimize AAM processing time to become an insignificant portion of the average ground TNC journey.

4.4. Limitations

The forecasted demand was for the Uber Elevate use case only. That is, the forecast did not include potential demand for air taxis that may shift from other modes such as walking, micromobility, private vehicle, and other modes of public transportation. The model utilized a forecasted population for 2030, TNC statistics, and criterion from previous studies that assessed the potential for mode shift from ground TNC rides. Those TNC statistics could change over time. If so, the analyzed scenario can represent a baseline scenario for comparison. Additional research could survey trip purposes in smaller transportation analysis zones (TAZs) to forecast the potential for additional mode shift. However, agencies must weigh the additional cost of doing such surveys on a local scale to estimate demand more accurately.

The cities and routes selected were based only on the potential of their population to generate more than two daily departures of four-passenger drones. The analysis did not consider additional criteria such as recurring congestion levels that slow ground traffic,

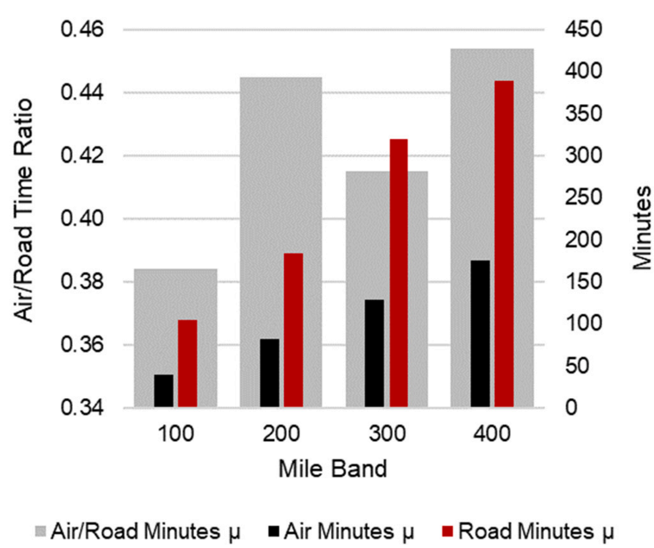

Fig. 4. Average travel time savings with drones for each distance band.

sociodemographic factors that can affect affordability, and the potential for induced demand. TNC users often pay additional fees for airport access (Gurumurthy and Kockelman, 2021). Therefore, it is possible that faster access and processing times to fee-free vertiports would induce demand.

The operating hours of 6 a.m. to 8 p.m. for first and last departures, respectively, represented a scenario where drone operations will cease when it becomes dark. Longer operating hours can reduce the number of drones needed to service daily demand for some routes. Furthermore, this analysis constrained the maximum vertipad departure capacity based on limitations of current battery charging technologies. The scenario was that the total time required for disembarking, cleaning, and boarding will be comparable to the charge time. Shorter charge time that reduces the vertipad occupation time can increase vertipad capacity to service a greater daily demand with the same number of drones and vertipads. Shorter charging time will also increase aircraft utilization by reducing time parked on the ground. Higher aircraft speed will further reduce the time savings ratio and potentially induce further demand.

Analysis of the specific placement of vertiports within each city was not within the scope of this study. Analysis of fare strategies based on willingness-to-pay (WTP) was also not within the scope of this study. Future work will conduct case studies of vertipad capacity maximization based on sharing routes and location optimization based on zonal TNC demand.

5. Conclusions

Analysts and investors predict that advanced air mobility (AAM) will disrupt urban and regional travel by distributing aircraft access across cities, closer to where passengers would need them. The new electric vertical takeoff and landing (eVTOL) aircraft can access small spaces called vertipads like a helicopter and cruise efficiently at high speeds like a winged aircraft. Advancements in distributed electric propulsion promise to increase safety and reduce engine noise to levels comparable with urban traffic. Further advancements in battery technology and lightweight airframe materials will increase operating range beyond 100 miles. Aircraft technology and safety regulations are steadily progressing. Amid those developments, uncertainties about eVTOL range capability and widely varying market forecasts raise questions about where to first deploy commercial services to capture the greatest latent demand.

This research combined top-down and bottom-up approaches to forecast demand for air taxis based on the Uber Elevate use case. The top-down aspect forecasted the population for all U.S. cities in 2030, used known trip rates for ground TNC rides, and the anticipated propensity to shift modes to air based on trip length statistics. The bottom-up aspect used a geographic information system (GIS) and network trimming techniques to identify all potential routes between cities that fall within distance bands of 100 to 400 miles, in 100-mile increments.

The main findings were that service providers will need 3023 four-passenger eVTOL aircraft to fly approximately 78 thousand passengers daily across 2083 urban and regional routes. Initial deployments that target routes within the first 100-mile band will access the largest available market in terms of daily passenger volume. However, serving longer routes of up to 400 miles will increase aircraft utilization and require fewer aircraft and vertiports. The capital needed to acquire aircraft and build vertiports to serve routes within the first 100-mile band will be a factor of two and five times larger, respectively, than for longer routes. The top ten routes across all distance bands were within the largest U.S. metropolitan areas within the U.S. states of California, New York, and Texas. The mean passenger years saved daily from ground-only travel was 2.4 in the first 100-mile band and accumulated to 10.1 in the 400-mile band.

Stakeholders involved in AAM market development can utilize the hybrid methodology to forecast demand for other regions of the world and for other use cases. Using known population, TNC statistics, and criterion based on distance thresholding can reduce forecast discrepancies, especially for a specific use case. Future work will optimize vertipad utilization and location based on case studies of zonal TNC demand. Future work will also extend the hybrid methodology to forecast route opportunities for eVTOL freight service.

CRediT authorship contribution statement

R.B.: conceptualization, methodology, software, data curation, formal analysis, writing—original draft preparation, reviewing and editing.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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This paper has not been submitted elsewhere in identical or similar form, nor will it be during the first three months after its submission to the Publisher.

Declaration of competing interest

The author has no relevant financial or non-financial interests to disclose.

Data availability

The sources of the datasets used in this study are cited within the manuscript, and they are all publicly available.

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