



# Progress in Vertiport Placement and Estimating Aircraft Range Requirements for eVTOL Daily Commuting

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In this paper, we consider the problems of vertiport placement and of estimating aircraft range requirements to serve passenger demand for daily commutes in eVTOL aircraft. Census data products including LODES and ACS are used to estimate daily commuting origins, destinations, and times. This data is used to place vertiports by solving an integer program that maximizes the population-cumulative potential time savings compared to driving. We also examine potential eVTOL aircraft range requirements for commuting by determining straight-line distances connecting the vertiports placed through our optimization approach. The techniques are applied to UAM commuter networks in the San Francisco and Los Angeles metro areas.

## I. Introduction

Urban Air Mobility (UAM) is an emerging class of transportation that is envisioned as a low-cost, on-demand, point-to-point passenger air service with flights between rooftop “vertiports” situated throughout cities. UAM will likely be realized by a new class of aircraft that are (1) highly automated or wholly autonomous, (2) electric or hybrid-electric, with battery energy storage and electric motors for propulsion, and (3) capable of vertical takeoff and landing (VTOL). These electric VTOL (eVTOL) aircraft will be managed in a sophisticated network operation that interfaces with the complex airspace in cities and is optimized to achieve high throughput, low costs, low community noise, and high levels of safety. The concept of eVTOL UAM was popularized largely by Uber in a 2016 white paper announcing their intent to enter the UAM market [1].

Intra-city passenger air service in the context of UAM is envisioned to serve trip purposes including airport transfer, leisure trips, and daily commuting to work [2]. In this paper, we consider how vertiports should be placed within cities to maximize the time savings potential of UAM compared to driving for daily commuting. Our approach extends a prior vertiport placement approach by considering not only the household population distribution but also work locations [3]. We also examine range requirements for eVTOL aircraft intended for commuting trips.

## II. Modeling Potential eVTOL Commutes with Census Data

Data from three different sources are considered in this study. The first data source is the American Community Survey (ACS), prepared by the U.S. Census Bureau [4, 5]. The ACS is a rolling survey of approximately 3.5 million households per year, with data published in single-year or past-five-year estimates. The variables surveyed by the ACS that are relevant to our problem of modeling commutes include population, household income, mode of transportation for commuting, time leaving home to go to work, and travel time to work. ACS data is published only as aggregated statistics – individual data points are not available. Because of this, certain correlations between variables cannot be determined. For example, the ACS publishes a data table that contains both earnings and mode of transportation, so this correlation can be explored, but the data set does not provide a table indicating time leaving home to go to work and travel time to work, so this correlation cannot be explored. All ACS data used in this study are from the 2012–2016 5-year estimates.

The second data source is the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) survey [6]. This data set provides detailed information that can be used to infer “origin-destination”

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home-work pairs: for each ordered pair of census blocks, the LODES data tells how many people live in the “origin” block and work in the “destination” block. However, caution is needed in interpreting LODES data for understanding commuting because unlike ACS, LODES data is based on administrative records, not surveys of workers themselves. One consequence is that the LODES data does not directly measure commutes, since there is no guarantee that the destination address is co-located with the worker’s office (vs., e.g., a company’s headquarters) or that the worker does not work remotely. Nevertheless, the LODES data is the closest surrogate for point-to-point commute counts that is freely available, and we consider it to be sufficient for this study, when used with caution and after applying relevant filtering.

The third data source is the TIGER/Line data sets from the U.S. Census Bureau which provide geographical boundaries for the census blocks and tracts [7]. TIGER files were used to prepare the maps in this paper and to identify interior points within each census block for the purposes of calculating straight-line block-to-block distances that are used to model flight ranges.

#### A. Estimating current commute time and number of commuters

For each pair of census blocks,  $(H, W)$ , the LODES data provides a count of the number who reside in block  $H$  and whose work address is in block  $W$ . Because of the small size of a census block, these pairwise counts are usually only one or two people. As discussed above, this data is not exactly equivalent to the number of people who commute between blocks  $H$  and  $W$ , since it does not guarantee that the person’s physical place of work is at  $W$ , only that their employer’s recorded address is at  $W$ . We describe how we account for this discrepancy below.

First, however, we compute commute distance and time measures between  $H$  and  $W$ . We treat each census block as a single latitude/longitude point, corresponding to the “interior point” datum listed in the 2017 TIGER/Line shapefiles. This is not necessarily the centroid of the block; it is only guaranteed to be a point inside the block. Denoting these points  $h$  and  $w$ , we compute the “flight distance” between the census blocks,  $d_{h,w,air}$  using the haversine formula. This represents the potential shortest path from  $H$  to  $W$  using eVTOL service, but is not a good estimate of the current commute distance by car. The drive distance by car,  $d_{h,w,car}$  is estimated by using the open source GraphHopper routing engine and OpenStreetMap data to calculate turn-by-turn driving directions from  $h$  to  $w$  – similar to those provided by any GPS navigation app. This provides  $d_{h,w,car}$  as well as an estimate of the driving time,  $t_{h,w,car}$ .

#### B. Modeling traffic

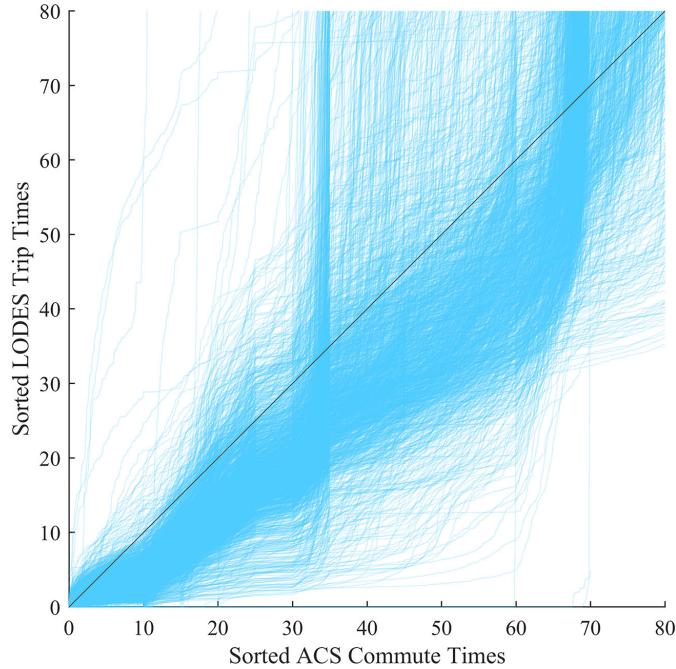
The driving times calculated by GraphHopper are primarily based on speed limits and do not take into account traffic. In order to simulate the effect of traffic, we scale the drive times obtained from GraphHopper to more closely match the driver-reported commute times in the ACS data. Recall that the ACS data provides a distribution of commute times as reported by respondents, but does not provide information on the destination of their commute. For this analysis we use the ACS data for commute time by mode of transit (ACS table B08134), considering only the mode “car, truck, or van.” We do not further reduce our consideration to only those who reported driving alone at this step.

The ACS data gives the number of respondents who report commute times within differently-sized bins between 0 and 60 minutes. All commutes over 60 minutes are grouped into a single bin. Our first step in scaling the commutes is to reproduce a population of commutes from the binned ACS data such that the binning of this population matches the distribution found in the ACS data. First, we scale the counts in the ACS data to match the count of trips we have in the LODES data. (All we are concerned with in the traffic scaling analysis is the *distribution* of times and this allows for a simple 1-to-1 comparison between the data sets; we correct for the count of commuters in the final analysis as described below.) For example, if the total ACS count of commuters who reside at  $H$  and commute by car, truck, or van is 1000, and the count of LODES trips originating at  $H$  is 1500, we multiply all ACS bin counts for  $H$  by 1.5 so that we sample an artificial ACS population of 1500 members.

Next, we sample the population by simply assuming a uniform distribution of commute times within each bin. For example, if for a particular census tract, our corrected bin-count for the “15-19 minutes” bin is 253 commuters, we add 253 uniformly distributed values between 15 and 20 to our artificial ACS population. (We use 20 rather than 19 because 20 is the lower limit of the next bin; ACS data is rounded to the nearest minute but our population is not.) For the 60+ minute bin, we use the 98th percentile of the LODES/GraphHopper trip times as the bin’s upper limit for the purpose of sampling.

We now have two sampled populations of commute times originating at  $H$ : The reconstructed ACS population described in this section, and the drive times obtained with GraphHopper and LODES data described above. Sorting each of these populations and plotting them against each other for each origin census tract yields the image in Figure 1 for the San Francisco metro area. In this plot, each (monotonically increasing) curve represents the commutes originating

from one of the 1800 census tracts in the study area. Two effects are prominently seen. First, the bulk of the curves fall below the one-to-one parity line of a perfect fit. This indicates that, in general, the ACS-reported commute times are longer than the LODES/GraphHopper calculated driving times. This result is expected because the GraphHopper routing is based on OpenStreetMap data that does not contain traffic information (only speed limits); therefore, our LODES/GraphHopper calculation underestimates actual commute times. This trend confirms our motivation for correcting the drive times to account for traffic by calibrating to ACS-reported commute times.

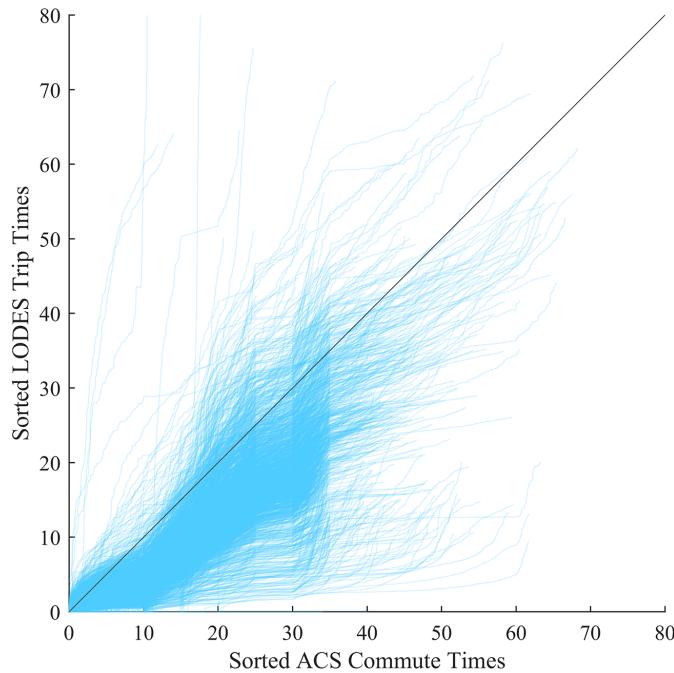


**Fig. 1** Sorted reconstructed ACS commutes vs. corresponding LODES trip time computed with GraphHopper

Second, we see that many of the curves become nearly vertical as time increases. This behavior indicates that the GraphHopper results are vastly *over-estimating* the commute time for these cases. We believe this is because of the aforementioned shortcoming in the LODES data – it lists the workplace according to administrative records, not a worker-reported job site, implying that it includes some reported workplace locations that are far from actual work locations, perhaps even several states away. For example, Figure 1 has many nearly vertical lines near  $x = 35$ . This trend indicates that no commuters in these census tracts reported commutes exceeding 35 minutes in the ACS, but according to the LODES records, some of their workplaces are far enough away that it would take >80 minutes to drive. The workplace records in LODES for these commuters apparently do not represent the commuters' actual workplace.

To overcome this shortcoming, we discard the top 30% of data points with respect to commute time within each census tract when computing the effect of traffic. In other words, our traffic calculation is based only on shorter-distance trips, which are more likely to represent actual commutes. Trimming the data in this way also avoids the difficulty of modeling the ACS bin for commutes of 60 minutes or greater, for which the upper limit is unknown. (As stated above, we model this upper limit as the 98th percentile of the trip times computed from LODES.) A similar plot to Figure 1 for this reduced data set is shown in Figure 2, which does not exhibit the problematic sharp increases seen previously.

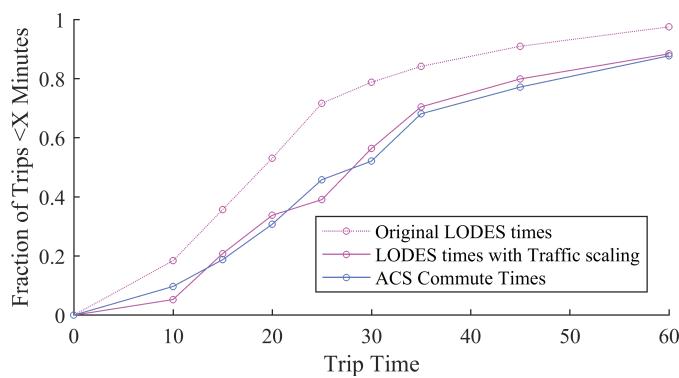
Finally, from these trimmed populations, we calculate a traffic scaling factor for each census tract by using a least-squares fitting procedure to calculate the scalar value  $s_H$  that minimizes the squared errors between the  $i$ th member of the populations of the reconstructed ACS data and the corresponding member of the LODES trip data, summed over all  $i$ . This computation is completed independently for each census tract, yielding a different traffic scalar for each tract. The LODES trip times, computed using GraphHopper, are then multiplied by this scalar to obtain the final effective driving time between each pair of census tracts. The resulting driving times between tracts are those that will be used in



**Fig. 2** Sorted reconstructed ACS commutes vs. corresponding LODES trip time computed with GraphHopper

our vertiport placement optimization.

The effect of the traffic scalar is easily illustrated with an example. Figure 3 shows the cumulative distributions of commute times for a representative census tract in the San Francisco area. The LODES/GraphHopper data is binned according to the same commute times used in the ACS data; the ACS curve shows the actual ACS data, not the reconstructed population. The curves show that the scaled LODES/GraphHopper trip times data much more closely matches the distribution of commute times reported in the ACS data than the unscaled LODES/GraphHopper trip times, which severely underestimate commute times.



**Fig. 3** Effect of traffic scaling on modeled commute times for a single census tract

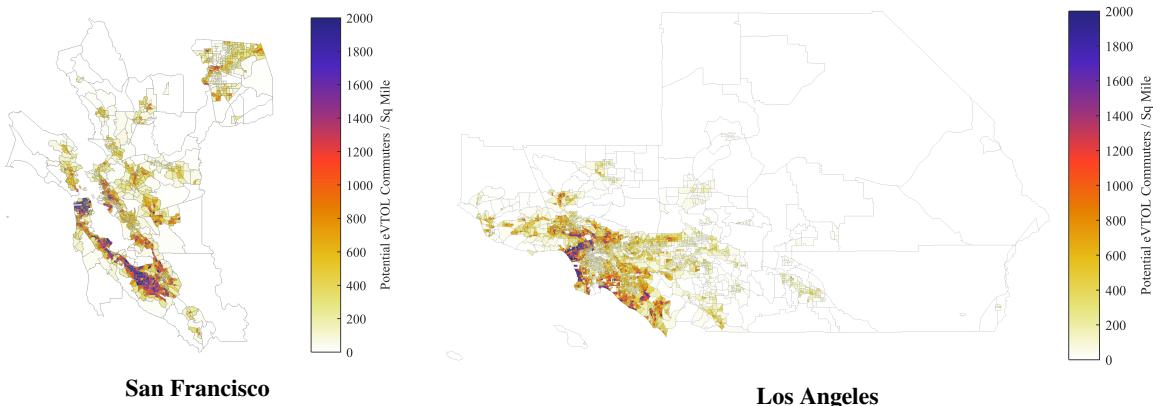
One shortcoming of this approach is that it applies the same scaler to all trips from the home census tract. Consequently, it attributes traffic to the location of a person's home, rather than with the route they travel or the location of their work.

### C. Modeling the number of commuters

Next, we scale the LODES counts to attempt to better represent the actual number of people commuting, and even further, to represent the number of people who would be potential eVTOL riders. First, we scale the counts so that the total number of counts originating at  $H$  matches the corresponding ACS total estimate of commuters whose home is in  $H$ . Next, we reduce this number to attempt to better represent the potential eVTOL passenger pool. For the purpose of this study, we assume the potential eVTOL passenger pool to be comprised of high income individuals who currently drive to work alone. We assume that there is no relation between income and driving alone, and distance or time of commute, so we simply multiply every LODES count originating at  $H$  by the same scaling factor to uniformly reduce the counts. ACS data table B08119 provides counts of commuters split by mode and income level; from this data, we use the count of commuters who drove to work alone and who have an individual annual earnings greater than \$75,000. Our model for the final effective count of potential eVTOL commuters is

$$count_{H,W} = (\text{LODES count from } H \text{ to } W) \frac{(\text{Total ACS commuters from } H)}{(\text{Sum of LODES counts from } H)} \frac{(\text{ACS drive alone + } >\$75k)}{(\text{Total ACS commuters from } H)}$$

Generally, this estimate will be a decimal number, which may be thought of as the “typical” number of daily trips by high income individuals driving alone on any given day. The geographical distribution of potential commuters is shown in Figure 4.



**Fig. 4 Density of potential eVTOL commuters, defined as individuals with annual earnings greater than \$75,000 who drive to work alone**

### D. Data modeling summary

For the purposes of this study, we assume that the typical near-future eVTOL commuters will be people who have a high income, currently drive alone, and have a long-duration commute relative to the straight-line distance between their home and work. In order to model these commuters, we need to know several things: How many high income commuters that drive alone live in each census tract? Where do they commute to? And how long does their commute currently take? The number of high income commuters is directly estimated by the ACS data. The question of where they commute to is not directly answered by any census data set, but is most closely approximated by the LODES data, which lists workplace addresses according to administrative records. Finally, the question of how long the commute takes is the most difficult to answer. ACS provides distributions of commute times for each home census tract, but does not show where each commuter is going. LODES provides information about where people are going, but not how long it takes to get there. We have used the LODES location data as an input to a driving-directions algorithm, GraphHopper, based on OpenStreetMap data, to approximate a driving time for each trip. We then scale these driving times so that their distribution more closely matches the self-reported commute times in the ACS data.

Finally, we note that the LODES data used was tabulated at a census-block level, while the ACS data is available only at the coarser census-tract level. The block-level LODES data was used while calculating the commute distances and times with GraphHopper, since it provides more accurate estimates of locations. After these calculations were

completed, we aggregated the block-level commute data to the tract level by taking the count-weighted average. This tract-level data was then used to compute the traffic scalars and throughout the rest of the study.

### III. Modeling an eVTOL Commuter Network for Optimization

From the data described above, we formulate a (binary) integer programming optimization model to place vertiports to optimally serve the potential commuters.

To formulate the problem, we discretize vertiport placements by allowing a vertiport to be placed in each census tract; i.e. there is one variable per census tract representing whether or not it contains a vertiport. Each vertiport is presumed to have unlimited capacity; we later examine the resulting number of flight operations at each vertiport. Vertiports are allowed to serve not only their own census tract but all census tracts within a small neighborhood around them. This formulation ensures that the optimizer does not place too many vertiports in a nearby area when really one (larger) vertiport would suffice. This allowance is especially necessary because we limit the total number of vertiports that the optimizer may place. The “catchment” neighborhood around a vertiport is defined as the set of census tracts that are within 3 miles *and* within a 5 minute drive.

A second, much larger, set of variables represents whether the commute connecting each *pair* of census tracts can be served by eVTOL trips. These variables can only be set to “true” if there is a vertiport placed within the neighborhood of both the origin (home) and destination (work) census tracts. We simplify the problem by only creating these variables for pairs of census tracts separated by more than 30 minutes of driving (with traffic), reasoning that trips shorter than this threshold are less appealing as eVTOL flights. We also exclude any pair of census tracts with less than 0.1 potential eVTOL commuters per day.

The objective function of the optimizer is to maximize the cumulative time saved in commuting throughout the entire network. For each of the commute variables described above, we associate a value equal to the number of potential eVTOL commuters who live in the origin census tract multiplied by the time savings that would be achieved by completing this trip by eVTOL. In this study, we model the time required for an eVTOL flight as

$$4\text{min} + \frac{\text{Straight-line distance between census tracts}}{150\text{mph}} \frac{60\text{min}}{1\text{hr}}$$

presuming a 4 minute time total time for climb/descent and hover (inclusive of both takeoff and landing), a 150 mph eVTOL nominal cruise speed, no wind effects, and no routing penalty relative to direct haversine distance. This flight time is compared to the drive time with traffic to determine the time savings achievable with eVTOL.

We consider case studies for two cities, San Francisco and Los Angeles, and we complete three optimization studies for each city: a small network of 10 vertiports, a medium network of 20 vertiports, and a large network of 40 vertiports. The increase in number of vertiports may be thought of as approximating the growth of a network over its first several years of operation.

The optimization problems were modeled and solved using the Gurobi optimization solver. We ran the cases for approximately 4 hours on a modern 24-core workstation. These are very large, difficult to solve problems; they contain over a million variables since the number of variables scales as (number of census tracts)<sup>2</sup>. They are also poorly bounded by their linear relaxation. The poor bounds make it difficult to tell how well the optimization solver has converged to the (global) optimal solution. However, since we see similar geographical patterns in the different-sized cases, we are confident that the results are representative of “good” networks, even if they may not be strictly “optimal.”

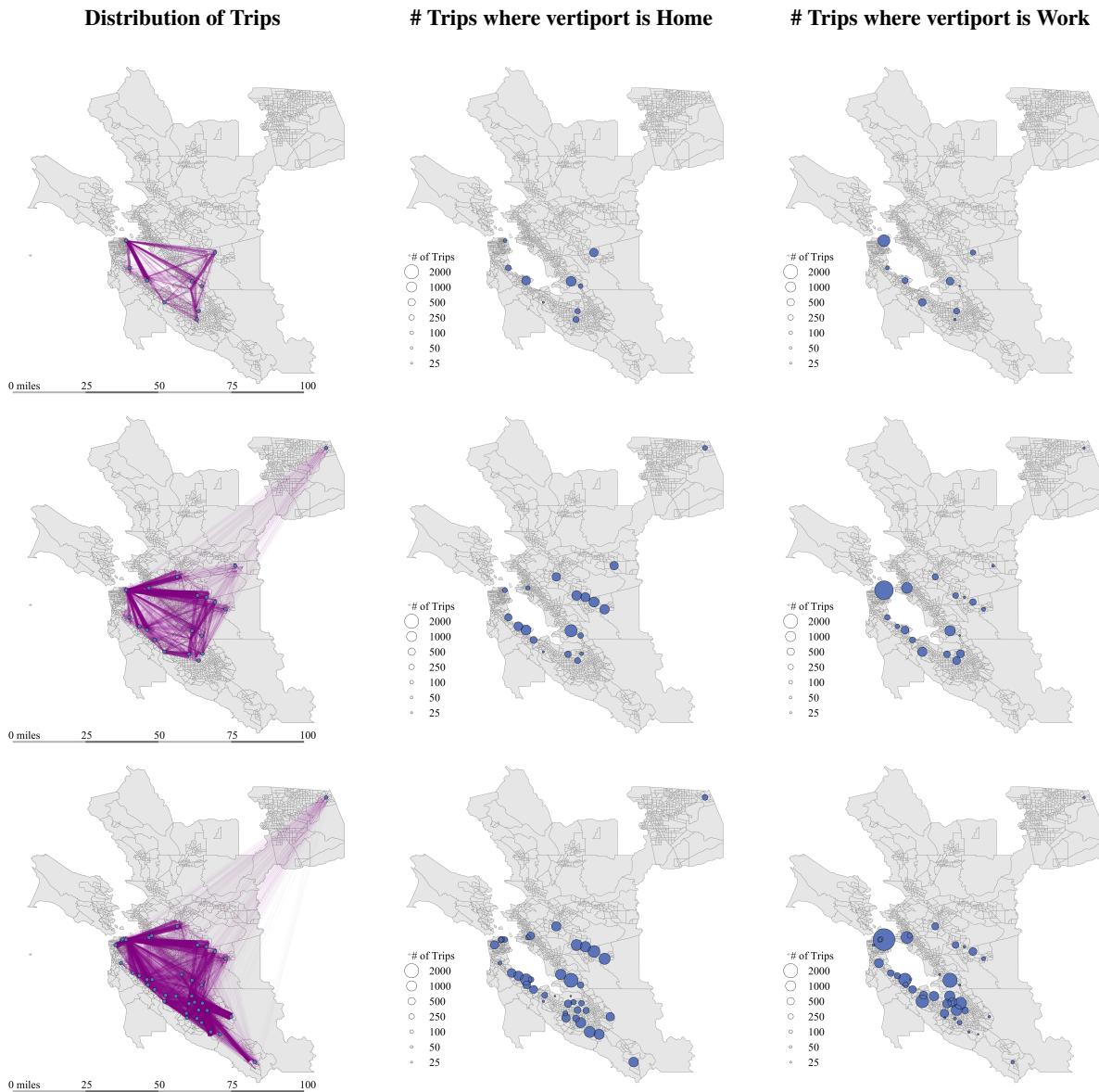
### IV. Results

Results of the case studies are shown in Figures 5 through 7. In Figures 5 and 6, the blue dots show the locations of vertiports placed by the optimization algorithm. In the second and third columns, these dots are sized according to the number of potential trips (i.e. the number of trips if all of the potential commuters were served) for which that vertiport serves as the commuter’s “home” or “work” location. In the first column, the purple lines show connections between census tracts of eVTOL trips served by these vertiports. Thicker, darker lines indicate more trips being flown between the corresponding tracts. Note that these lines are drawn to connect the commuter’s home and work tracts, which may be any tract within a 5 minute drive of the vertiport location.

Figure 5 shows the results of the San Francisco case study. Each row of the figure shows one of the three networks considered: small, medium, and large. The results show that the most appealing trips based on the existing census commute data are relatively short range trips around San Francisco Bay. For “work” destinations, downtown San

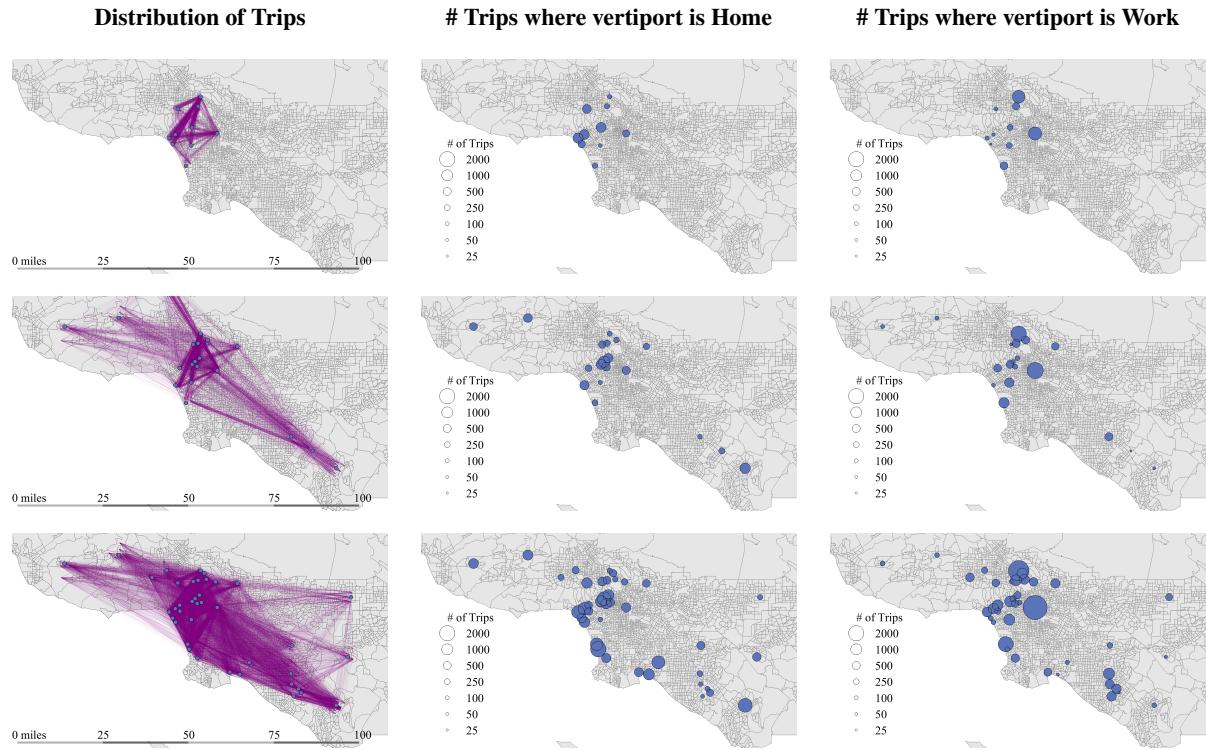
Francisco, near the Financial District, is the most important vertiport location. The “home” locations are more evenly spread around the metro area. Notably, few home-work trips originate from downtown San Francisco. This is to be expected – people who live downtown probably also work downtown, and therefore have little need for an eVTOL service in the context of commuting.

As the network size is increased, we see a few outlying vertiports, with one placed near Sacramento and another situated south of San Jose. Although the Sacramento vertiport is only lightly used, it serves the longest possible commutes in the area, so it offers great benefits to its passengers.



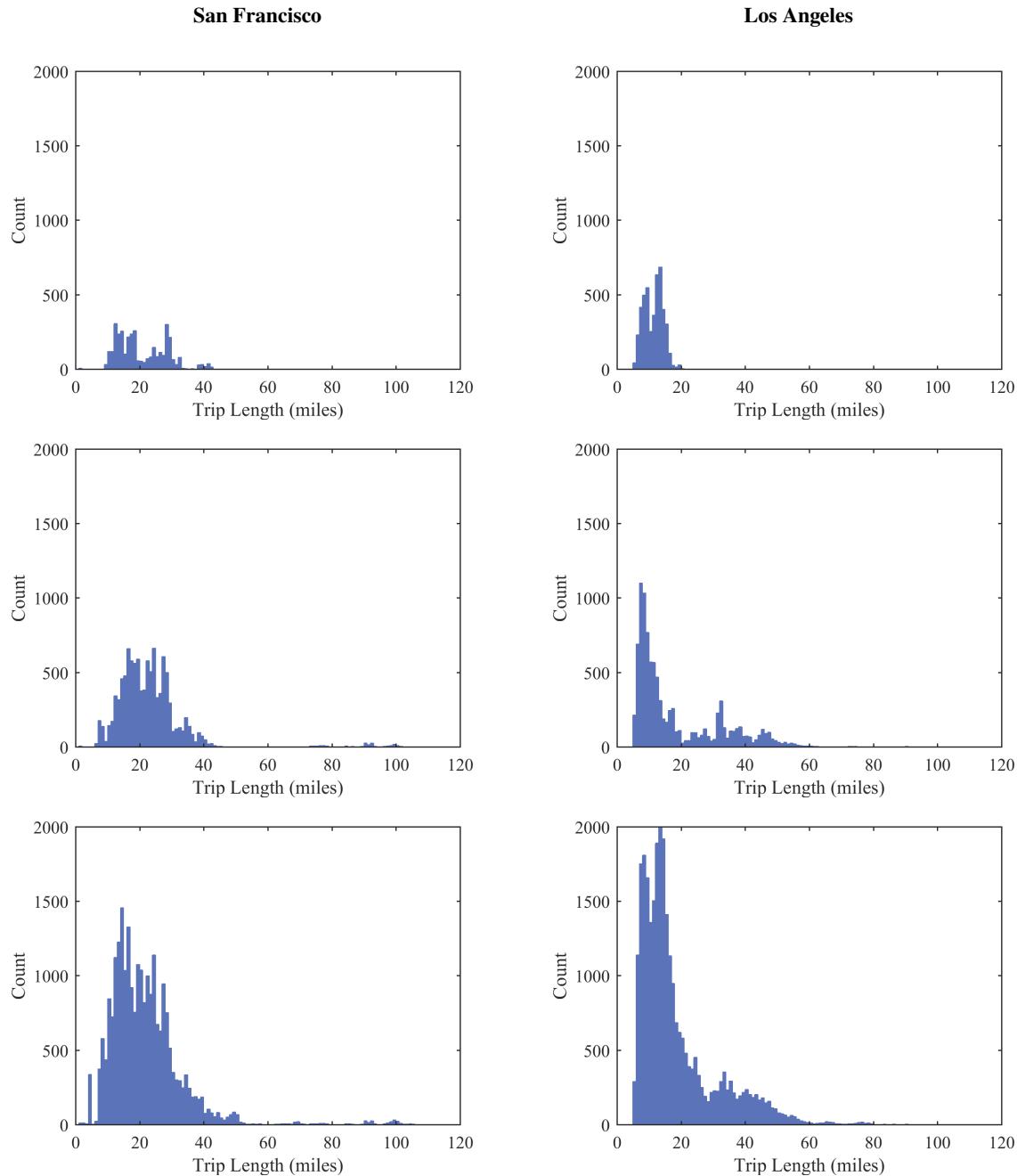
**Fig. 5 Optimization results for San Francisco area. Row 1: Small network; Row 2: Medium Network; Row 3: Large Network**

Figure 6 shows the results for the Los Angeles case studies. Somewhat surprisingly, the network is very strongly aggregated in a small area around Santa Monica, Burbank, and downtown Los Angeles. Comparing with the distribution of likely commuters shown in Figure 4, this seems to be explained by the density of the high-income commuters in these areas. The ranges of flights in this central cluster are generally very short – as little as 5 miles. However, the severe traffic in the area can make even such short trips difficult by car. As we increase the network size, we begin to see more flights serving the outlying areas, but the strongest growth in eVTOL use remains in the central area.

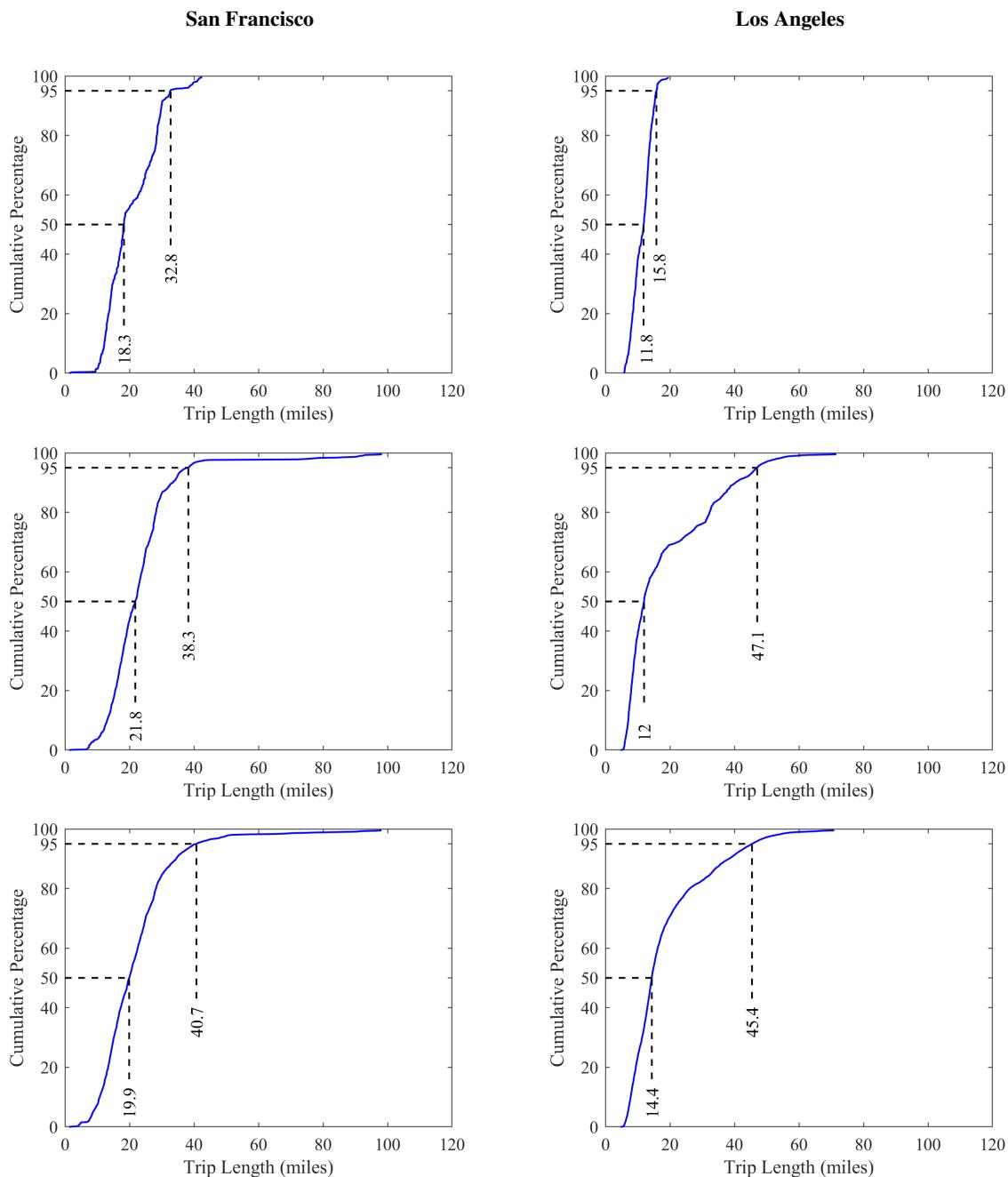


**Fig. 6 Optimization results for Los Angeles area. Row 1: Small network; Row 2: Medium Network; Row 3: Large Network**

Figure 7 and Figure 8 show the distribution of haversine ranges in trips servable by eVTOL for each of the six cases. Detour penalties based on airspace restrictions or other considerations are not modeled. These results show that regardless of network size, short trips under 30 miles dominate the eVTOL commuter market in these cities. Only a few trips extend beyond 60 miles. However, since this study is based on existing census data records, the ranges are skewed toward where people live and work now. Likely, once an eVTOL service is in reliable at-scale operation, people may choose to move farther away from their jobs, resulting in longer-distance commutes.



**Fig. 7 Distribution of ranges of trips served by eVTOL. Row 1: Small Network; Row 2: Medium Network; Row 3: Large Network**



**Fig. 8 Cumulative distribution of ranges of trips served by eVTOL with indication of 50th percentile (mean) and 95th percentile ranges. Row 1: Small Network; Row 2: Medium Network; Row 3: Large Network**

### Acknowledgments

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