This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

A Traffic Demand Analysis Method for Urban Air Mobility

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***Abstract*— This paper explores the addressable market for Urban Air Mobility (UAM) as a multi-modal alternative in a community. To justify public investment, UAM must serve urban mobility by carrying a significant portion of urban traffic. We develop a traffic demand analysis method to estimate the maximum number of people that can benefit from UAM, for a given use case, in a metropolitan region. We apply our method to about three hundred thousand cross-bay commute trips in the San Francisco Bay Area. We estimate the commuter demand shift to UAM under two criteria of flexibility to travel time savings and three criteria of vertiport transfer times. Our results indicate that even for commuters with high value of time, and long transfer times at vertiports, almost forty-five percent of demand would benefit from UAM when the roads are highly congested. Even when the roads are mostly free, about three percent of the demand can benefit from UAM with the right combination of commuter flexibility and transfer times. Finally, our method also produces the number, location and distribution of demand over vertiports that can support value proposition, policy-making and technology research for UAM.**

***Index Terms*— Urban air mobility, unmanned aircraft systems, traffic demand analysis, vertiports.**

I. Introduction

ALL mobility is door to door. Some doors are small, others larger like commercial centers, hospitals, schools, airports, ports, or train stations. People make these trips uni-modally walking, driving, carpooling, or cycling, or multi-modally using a service such as buses, rapid transit, Uber Express or ferry, in conjunction with one or more of our uni-modes. This paper explores the addressable market for UAM in the multi-modal travel paradigm. To justify public investment, UAM must serve urban mobility by carrying a significant portion of urban traffic.

Therefore, we ask, what is the maximum number of people in a metropolitan region that can benefit from UAM? We develop a method to answer this question based on traffic demand analysis of a metropolitan use case for UAM. This paper presents the method with a sample application to a metropolitan region use case. When a traveler chooses a mode, the traveler pays in time and the provider in costs. Being focused on UAM as a public good we eschew matters of profit, fare, or subsidy at this time and explore UAM relative to other modes only with regard to the incurred travel time by the traveler and the costs by the provider. Furthermore, since the primary focus here is the traveller, the incurred costs by the provider are indirectly accounted for in terms of ridership numbers as explained in section III. The cost share breakdown and its augmentation or recovery by fare, profit, or subsidy are a matter of business model and outside the scope of this paper.

Travel time and service cost are functions of the UAM vehicle technology, the fleet operation technology, available airspace and traffic management technology, vertiport operation technology, cost of construction and acquisition of the vertiports, contingency landing areas, cost of airspace monitoring, control, and safety assurance infrastructure [7], [15], [18], [19]. Given feasible assumptions on these dimensions, a traffic demand analysis can be done to determine the optimal number and location of the vertiports in a metropolitan region and the distribution of the demand over them. Our traffic demand analysis method is described in section III.

In this paper, we focus on a subset of commuter data for the San Francisco Bay Area as a sample application of our traffic demand analysis method to answer the aforementioned question. The data is described under section IV. A commuter can travel from origin to destination in two ways. First is uni-modally via road. Second is a multi-modal trip, where a commuter travels to the vertiport nearest to the origin via road, then flies to the vertiport closest to the destination and finally travels from there to the destination again via road. Each of these options has an associated travel time. Clearly, a commuter could choose the latter option if the travel time is shorter. But the travel time benefit comes at the cost of flexibility to the commuter. For example, the commuter gives up the flexibility of her car either beyond the origin vertiport or for the entire trip. This entails that the travel time advantage has to be significant compared to the first mode of travel to encourage mode shift.

The travel time benefit depends on the distribution (number and location) of the vertiports. The distribution also affects allocation of demand to the vertiports. Too few vertiports for a lot of commuters would impose demands much above the operational capacities. At the same time, if adding a vertiport to the system doesn't improve the ridership sufficiently,

Manuscript received April 2, 2020; revised November 7, 2020; accepted December 17, 2020. The Associate Editor for this article was E. Atkins.
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Digital Object Identifier 10.1109/TITS.2021.3052229

it cannot justify the costs of building and running the extra vertiport. We address this by first using a k-means clustering to determine the distribution of the vertiports for a given number. We then compute the travel times and identify the number of commuters benefited based on assumptions on transfer times and mode shift criteria. We repeat this by varying the number of vertiports, to estimate and check against the capacity and cost justification criteria to find the feasible combinations of vertiports and from that identify the maximum number of commuters (and the associated combination of vertiports) that can benefit from UAM.

An analysis like this is useful for different stakeholders. Public Metropolitan Planning Organization (MPO) and county transportation commissions and private investors can use this method for analyzing the value proposition of UAM use cases for a metro region. For policy makers such as the Federal Aviation Administration (FAA), this provides a basis for developing policies. A metropolitan region can be divided into demand centers using this method which consequently leads to the network design problems both on the land side and air side. Therefore, it also supports organizations like NASA and academic researchers to evaluate traffic management strategies or develop any of the aforementioned technologies that affect travel times and service costs.

The rest of this paper is structured as follows. We first present a review of related work that motivates this effort under section II. Section III lays out our approach in detail. The details of the chosen use case and sample application are discussed under section IV. In V we present the results of traffic demand analysis of the chosen use case. Section VI concludes this paper with our demand estimates for the SF Bay Area.

II. Literature Review

As a city grows in economic and cultural power its commercial and cultural districts rise in density. The residential ones do the same or sprawl. The effect on the single-person auto mode though is the same – it becomes less viable as a solo commute mode. In rush hour, a Los Angeles (LA) woman commutes in an average time of 30.5 minutes [4] because LA's rapid rail transit, the Metrolink takes as much as 28% of the traffic volume off parallel freeways [3]. An impressive 100,000 cars crawl the San Francisco-Oakland Bay Bridge at peak commute because another 70,000 people move through its rapid rail transit system's Transbay Tube cousin [1]. We are therefore motivated by the transit commuter who delivers a faster travel to the automobile commuter by undertaking an average commute trip of 36 miles at an average speed of 36 mph including stops [2]. The 30 minute excess borne by the transit commuter drives our interest in the mobility potential of UAM for the masses. UAM studies have pitched it as a solution for a high earning professional with very high value of time. However, we are interested in understanding if it has a value proposition for their lower income counterparts who are also long distance commuters. The value proposition to these commuter only gets sharper in the tails of the travel time distribution.

UAM market studies and reports [13]–[15], have explored large scale networks built of point-to-point services such as air taxis, air metro and last mile delivery. However, due to public acceptance, safety concerns and impact on legacy users, such large-scale networks will evolve starting with smaller and simpler use cases as steppingstones. [7], [9], [18], [19], [21] have explored the airspace integration barriers to UAM and hence addressed the problem from the supply side. They have shown improvements in urban passenger air travel time for both hub-door [6] like and door-door services with specific trip designs. Uber [15] estimates its future air taxis to be competitive to its current road based rideshare services based on time, direct operating costs and emissions. Our work complements these efforts for passenger movement. Furthermore, owing to its nascency, formal demand side analysis for UAM are lacking. Some recent promising efforts have focused on the low-altitude goods movement [12]. Our research therefore contributes more importantly to the demand side analysis of the equation.

For the demand analysis, the first step is to identify a use case and procure the trip data. In this paper, we focus on passenger movement use cases. To understand the impact of congestion on road movement times, Chan *et al.* [10] have developed a scalable transportation simulation using high performance parallel computing. This simulation is built on the San Francisco County Transportation Authority (SFCTA) Champ 6 model. It includes car trips only. They sub-sampled a selection of trips that crossed the Bay over three major bridges in a weekday. We acquired trip data from them for 327,579 of these commute trips. For reference, according to the SF Mobility Trends report [20], roughly there were roughly 1.5M trips every weekday on average in SF of which 456,000 were car trips. Our sample therefore represents about seventy percent of these car trips. The trip travel times are also an output of the simulation that models the congestion on the road network. We choose to account for congestion to make an optimistic estimate. A commuter who doesn't benefit from UAM in congested road conditions will clearly have a lower incentive during uncongested times.

Next step is to identify the number and location of the origin/destination vertiports, and allocation of the demand that maximizes its proportion that could benefit from UAM operations. The field of Facility Location Problems (FLP) is relevant for this [11], [17]. However, there is an inherent assumption of established roadway structure and a candidate set of potential facility locations and their capacities. Due to lack of an airway structure, we assume direct routes for the work in this paper. We do note that any airway structure would lengthen the UAM trip length and therefore duration compared to a direct straight path. This would only reduce the travel time benefit to users of UAM resulting in lesser people benefiting than the estimates produced by our method. However, since our goal is to find the maximum number of people that can benefit, our upper bounds will therefore still hold. Further, we take the uncapacitated FLP approach as described in III.

The speeds for road travel are provided from the use case data set of the 327,579 commute trips. In the absence of that, a reasonable assumption can be made from the fact that maximum permitted uncongested freeway speed in a US metropolitan region is usually 65 mph. On congested roads, the speeds come down to about 30 mph [5]. In comparison, urban air travel is envisioned to be most fuel efficient at speeds of about 125-150 mph [15] with operations at or below 5000ft altitude. However, to account for the slower climb and descent phases, we choose an average speed of 100 mph as described in the next section. The multi-modal UAM trip also entails additional transfer times for embarking and disembarking at vertiports, in addition to the first and last mile trips by road to the origin and destination vertiports, respectively. Even with pooling, these transfer times are expected to be kept under 15 minutes [15].

For the vertiport capacities, the maximum number is governed by separation requirements. Allowing at most two operations (takeoffs and landings) per minute (akin to high density runway capacities) with 4 passenger aircraft, amounts to about 500 passengers per hour per vertiport at peak. It translates to handling 12000 passengers per vertiport at most over 24 hours. This is the peak capacity constraint. In reality, this daily number will be less than 12000 because the peak hourly capacity would only be handled during peak commute hours. This therefore serves as an upper bound. We note that we chose this operations number based on our consultation with experts at NASA Ames Research Center. One of the busiest airports in the world - Hartsfield-Jackson, Atlanta has a runway capacity of about two operations per minute.

The additional daily passengers on the system brought by adding an extra vertiport should be significant enough to justify the high cost of building it. For this cost justification constraint, we look at rapid transit statistics. Bay Area Rapid Transit (BART) [1] handles 429,000 weekday passengers spread over 48 stations. This means that a BART station's cost is justified for bringing 9000 daily riders onto a transit system that carries around 10% of the daily commute traffic. If we assume that for public investment a vertiport transit network should handle at least 2% of commute traffic, this implies that an additional vertiport on the system should bring about 1800 more daily users on the system. This number therefore captures our cost justification constraint for the sample application in this paper. In other words, this is the threshold for the marginal increase in ridership on the UAM system by addition of an extra vertiport. We note that our traffic demand analysis method can be used with a separate number and it would still work. The results presented here are based on this sample assumption. We use the assumptions made in our approach, described next to estimate the demand that benefits from UAM.

III. Approach

The first step of traffic demand analysis is the trip data. There are several possible use cases for UAM passenger movement. These include short term deployments like an airport to airport shuttle or premium services like the Uber Copter for passenger with very high value of time. However, since we seek to understand UAM as a public good, we are interested in long term use cases. In this work, we focus on the daily commuters in a metropolitan region.

The daily commuter can travel from origin to destination, either directly by car via road or take a multi-modal trip, traveling to and from the intermediate mode's hubs by car. We think of UAM in this setting. A user of the system travels by car to the origin vertiport, flies from origin to destination vertiport, and then traverses the last leg of the journey by car. The data for the car trip can either be acquired empirically or via simulation. For the multi-modal trip, certain assumptions are necessary for transfer times and vertiport to vertiport travel time. These are listed under III-A.

We next select a range for the candidate number of vertiports, solve the location and demand distribution problem iteratively, compute the travel time statistics and compare them with the vertiport capacity and cost justification constraints to estimate the optimal demand. For solving the vertiport location and demand distribution problem we use an uncapacitated FLP formulation of the problem where we use the distance to vertiport from a trip origin/destination as the cost function and minimize the sum of the squared Euclidean distance to the vertiport. This simplifies to a k-means approach. We apply the k-means implementation in Matlab that uses the k-means++ algorithm [8] for cluster center initialization as it achieves a faster convergence than Lloyd's algorithm [16].

A. Assumptions

We make the following assumptions in our method. Since operational speeds of 125 mph to 150 mph are proposed for UAM, we assume an average speed of 100 mph for the vertiport to vertiport travel to account for the slower speeds of takeoff and landing. We assume that a minimum transfer time of 5 minutes is needed at each vertiport. We therefore vary the transfer time parametrically with a minimum of 5 minutes. The value of time for commuters depends on their flexibility to different modes. A long distance commuter with a low value of time might be fine with a 25% saving (15 minutes on a 1 hour trip) while a short distance commuter with a high value of time might need at least a 50% saving on travel time (15 minutes on a 30 minute trip). As described under literature review, we assume a capacity constraint of 12000 passengers per vertiport per day and a cost justification constraint of 1800 additional passengers benefiting from the system by adding an extra vertiport.

We make the following assumptions about the aircraft and their operations: (a) All aircraft are assumed to fly at an average speed of 100 mph vertiport-to-vertiport; (b) Their flight plans are straight line paths; and (c) The vertiports are served by 4 passenger aircraft. These assumptions only affect our capacity constraint and results specific to the use case chosen and not the method itself. We also note that actual flight trajectories might be longer and earlier operations might be at lower speeds. Both these only make the case worse for UAM on travel time. Since we seek to identify the maximum possible people that can benefit, our upper bounds based on the above assumptions still hold.

IV. Application

We apply our traffic demand analysis to 327,579 commute trips in the SF Bay Area. The data was procured by the

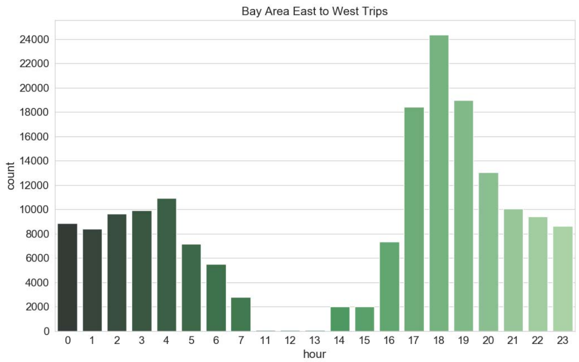

Fig. 1. East to west travel data for the SF Bay Area.

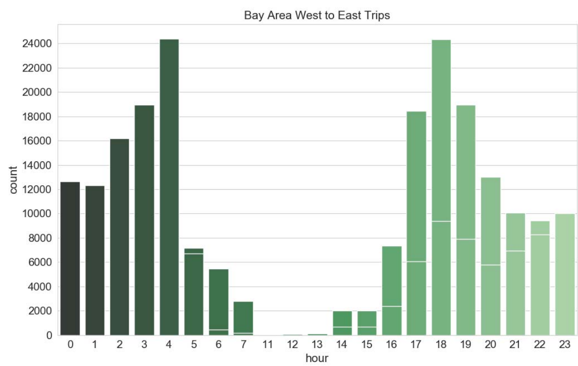

Fig. 2. West to east travel data for the SF Bay Area.

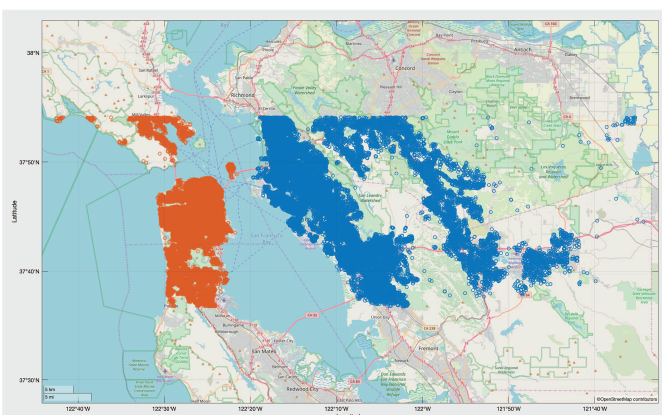

Fig. 3. Travel origins (blue) and destinations (orange) for East-to-West trips.

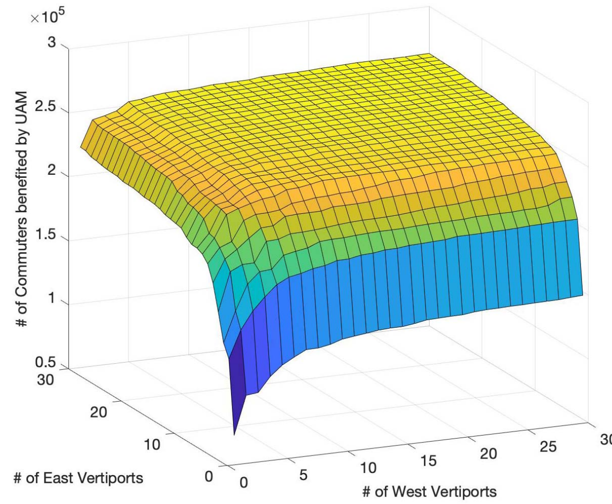

Fig. 4. Total commuters benefiting from UAM. Minimum 25% time savings. Transfer Time - 10 min.

Mobiliti team at Berkeley Lab from the SFCTA Champ 6 model. They then simulated the traffic under congested road conditions to derive the travel time and road distances that we use in our study. Each trip has an associated start time and therefore the demand varies through the day. Figures 1 and 2 show the distribution of the trip data over the day. Figure 3 visualizes the origins and destinations of the East-to-West (177,629 pairs) trips.

Given the origins and destinations, we can compute the direct haversine distance between them. Comparing with the actual road distances, gives us the distribution of the ratio of road distance to air distance for any pair of points on surface. Since we have the road distance and travel times, we can also compute the distribution of congested road travel speeds. Our UAM multi-modal trip has three legs: 1) Origin to vertiport near origin; 2) Vertiport near origin to vertiport near destination; and 3) Vertiport near destination to destination. To compute the travel times for the first and third legs, we use the above two distributions for distance and speed. For the second leg, we compute travel time from the haversine distance and aircraft speed. To this we add the transfer time twice to get the entire travel time of the UAM multi-modal trip for each commuter. We derive results for three transfer times - 5 min, 10 min and 15 min.

A commuter benefits from UAM if the time savings are at least 25% of their road travel time. This models commuters with a low value of time. To model commuters with a high value of time, we also estimate results with a require time saving of at least 50%. Hence, to summarize, we have 6 test cases derived from 3 cases of transfer times and 2 cases on minimum time savings as a fraction of car trip time.

V. RESULTS

We first present results for a particular case to explain our procedure. Figure 4 shows the total number of commuters benefiting by switching to UAM under the assumptions that a commuter switches if travel time savings are at least 25% of the car trip time given that the transfer time at each vertiport is 10 minutes. Figure 5 shows the top view of the same.

Next we take this data and estimate the average hourly operations at each vertiport for the east-west vertiport combinations. This is shown, for the above mentioned time saving and transfer time criteria, in figure 6 along with the 500 passengers per hour per vertiport constraint shown as a red surface. The same figure in top view (figure 7) shows us the feasible combinations of vertiports (the red region) based on the capacity constraint.

We note here that we use the term feasible mathematically, to mean combinations that remain in our analysis - the feasible set. The vertiport combinations not included in the feasible set

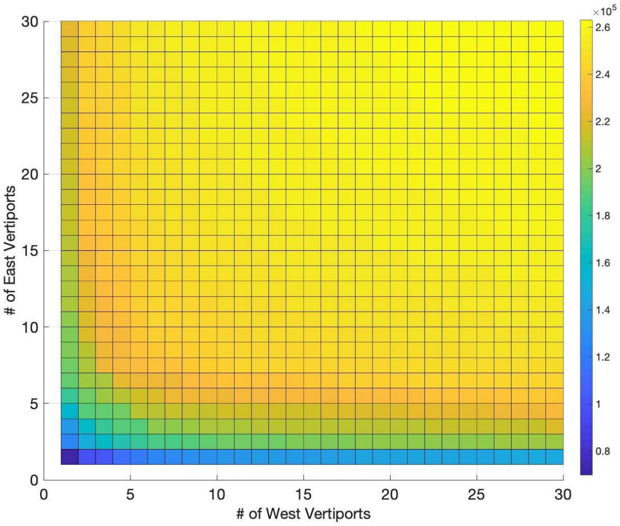

Fig. 5. Total commuters benefiting from UAM. Top View.

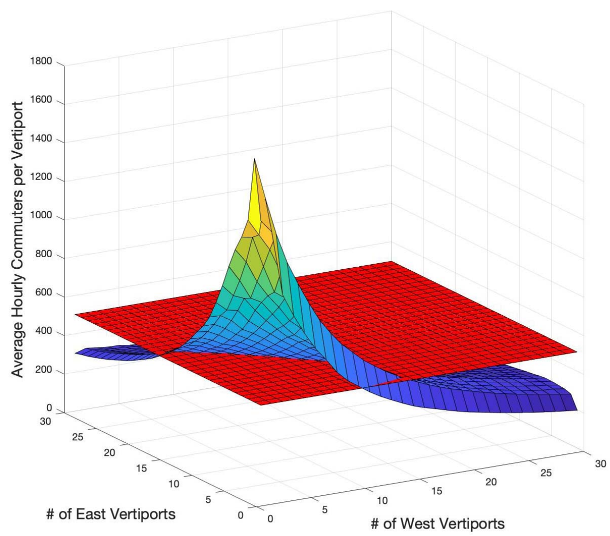

Fig. 6. Hourly commuter demand. Minimum 25% time savings. Transfer Time - 10 min.

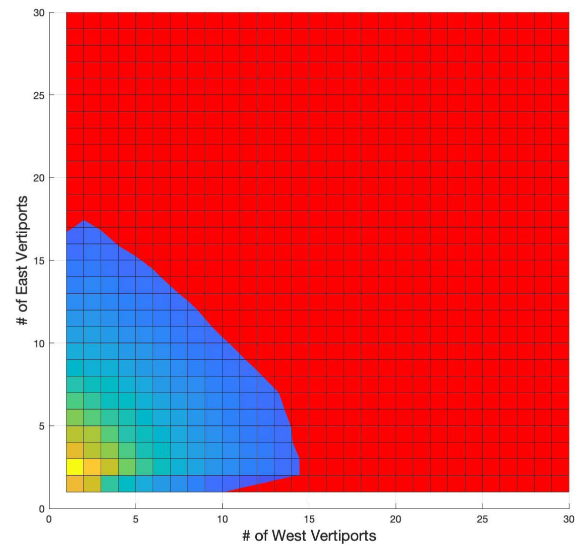

Fig. 7. Hourly commuter demand. Top View. Feasible region in red. The non red region would require some kind of demand management wherever possible.

TABLE I

MAXIMUM NUMBER OF COMMUTERS BENEFITED BY UAM AND THE CORRESPONDING VERTIPORT COMBINATIONS FOR SF BAY AREA WITH HIGH CONGESTION ON ROADS. THE NUMBERS IN PARENTHESIS ARE THE VERTIPORT NUMBER COMBINATION (EAST, WEST)

Time Savings % of Trip Time	**Transfer Time (minutes)**		
	5	**10**	**15**
25%	(30,5) 297,507	(16,27) 258,056	(30,7) 217,191
50%	(30,25) 258,075	(30,24) 201,319	(30,24) 155,600

for having very high demand could potentially be the most interesting from a service perspective. To throttle demand, an operator might need to turn away customers, increase fares or build strategies and infrastructure for simultaneous takeoffs and landing to increase capacity. In that sense, they are not necessarily practically infeasible. Instead, they require some level of sophisticated demand management wherever possible.

Now to apply the cost justification constraint, we have to limit the gradient of growth - the additional commuters benefited or the marginal increase in ridership by adding a vertiport. We look at every combination of vertiport and find the ones where at least 1800 commuters did not shift to the system either by adding a vertiport on the east or on the west. The combinations reached by addition of vertiport in such scenarios are therefore excluded from the feasible set. Combining this with the feasible set of vertiports from the capacity constraint, we get the overall feasible set. For the test case of 25% time saving and 10 min transfer time, this is shown in the top row second subfigure in figure 9. From this we identify the vertiport combination that supports the maximum mode shift to UAM for each test case.

We now discuss results across all the test cases. Figure 8 shows the feasible vertiport combinations for all test cases after applying the capacity constraint. Here the feasible set is shown in red. Next we apply the cost justification constraint also and show the overall feasible set for each test case in figure 9. The title of each subfigure lists the time saving and transfer time criteria of the test case. Note that the non-red regions are the feasible sets in figure 9.

The bands and islands of vertiport pairs in figure 9 are artifacts of the data set. Only combinations where marginal growth in ridership is above a certain number (1800 in our sample assumption) are considered feasible to justify the cost of adding an additional vertiport. Ideally, if this were repeated for multiple data sets and the gradient was smoothed by taking average growth in ridership over say hundreds of data sets, these islands would not exist. However, since this is done with just one data set, the islands and bands basically mean that the marginal growth from the previous combination was above the chosen minimum threshold of 1800.

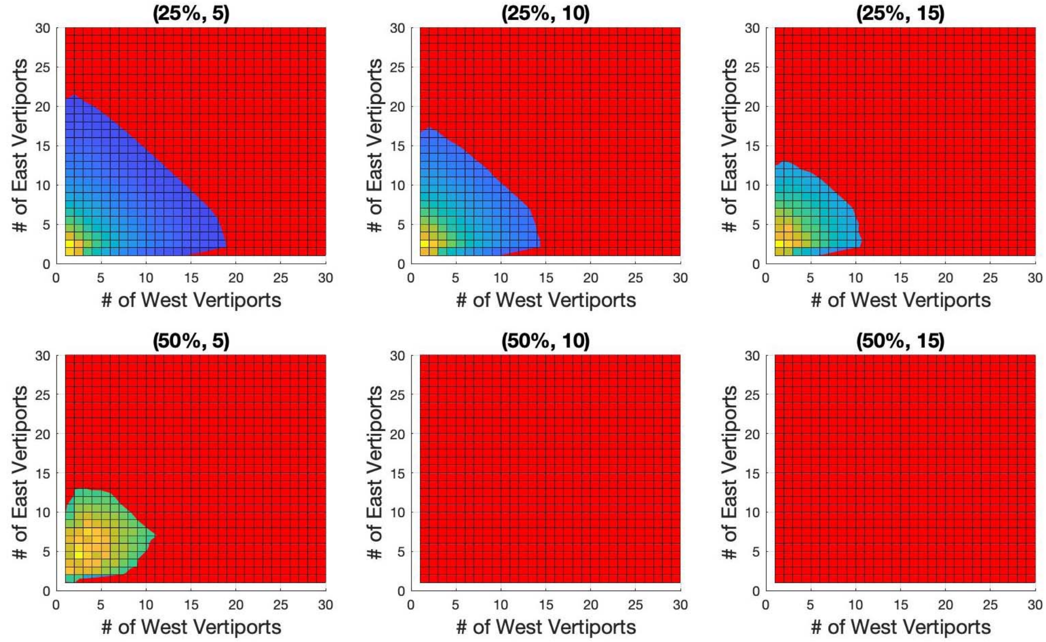

Fig. 8. The feasible set of vertiport combinations based on capacity constraint. Region with vertiport combinations that are not capacity constrained are shown in red. Subfigure title: (Time saving, Transfer Time in min).

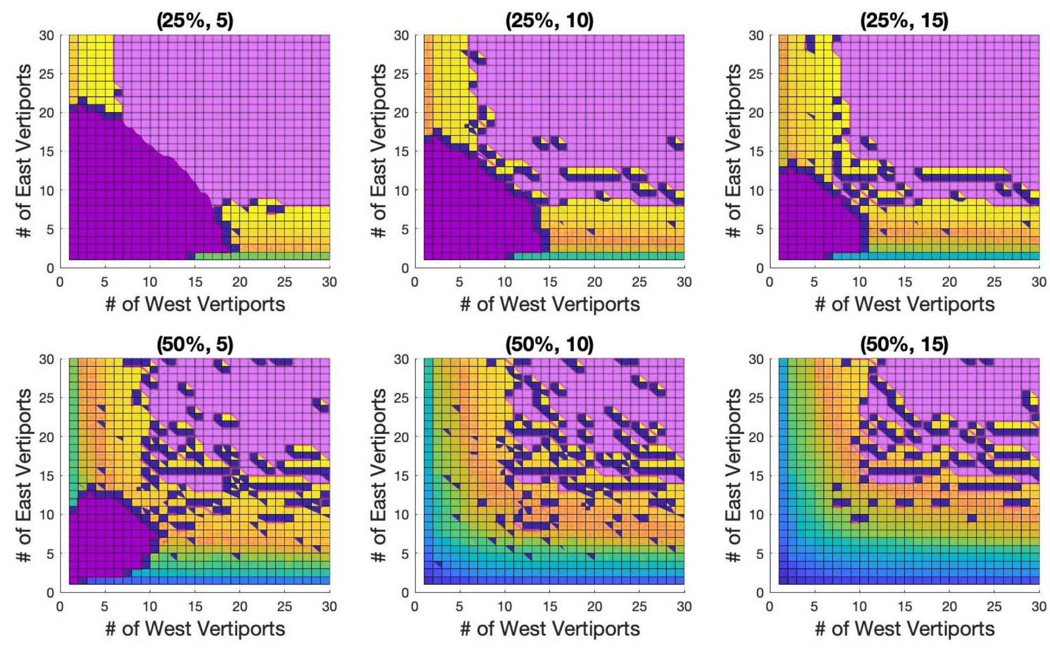

Fig. 9. The feasible set of vertiport combinations based on capacity and cost justification constraint. The capacity constrained region is shown in dark purple. Cost justification constrained region, where the marginal increase in ridership is not sufficient to justify the cost of building an extra vertiport, is shown in bright purple. Data for scenario where roads are highly congested. Subfigure title: (Time saving, Transfer Time in min).

From these figures we identify the maximum commuter traffic benefited and the corresponding vertiport combination in table I. The vertiport combination is shows as (East, West) number in the top row and the number of commuters benefited is shown in the bottom row.

We find that a major portion of the population is benefited by UAM. As expected higher flexibility and lower transfer time results in more commuters shifting to a multi-modal UAM trip. Even for commuters with a high value of time, who would only shift with fifty percent or higher saving in travel time and a high transfer time of 15 minutes at each vertiport, 155,600 commuters choose UAM. That is roughly 45% of the size of the data set. With the most optimistic assumption of 5 minutes transfer time and commuters with a

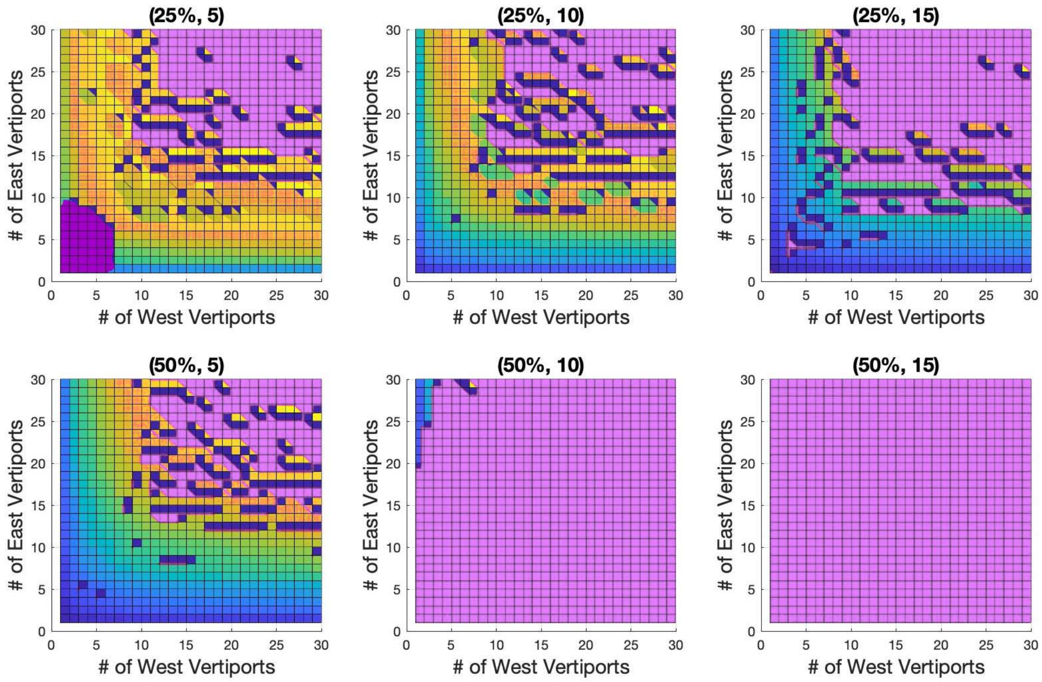

Fig. 10. The feasible set of vertiport combinations based on capacity and cost justification constraint. The capacity constrained region is shown in dark purple. Cost justification constrained region, where the marginal increase in ridership is not sufficient to justify the cost of building an extra vertiport, is shown in bright purple. Data for scenario where roads are uncongested. Subfigure title: (Time saving, Transfer Time in min).

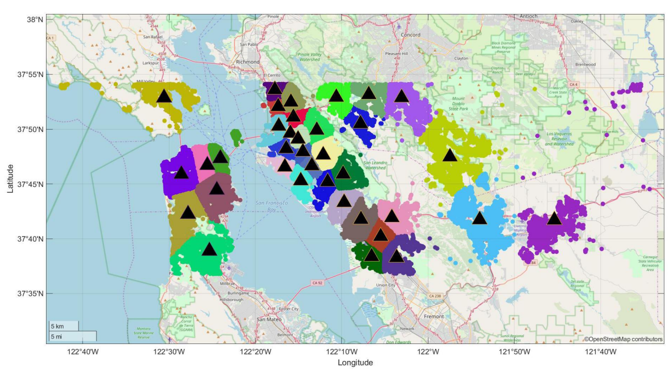

Fig. 11. Trips in SF Bay Area clustered by vertiports. 29 on East and 7 on West.

low value of time, almost 90% of the commuters benefit from UAM.

However, we note that this analysis used the congested travel times from the Mobiliti simulation. In reality, roads are neither congested 24 hours in the day nor are they free all the time. Hence, to measure the effect of varying congestion, we gathered uncongested trip times for the same origin/destination trip pairs from the Google Maps API. We used that to estimate a distribution of the ratio of congested trip times to uncongested trip times. Since the distance of the trip pairs is more or less fixed irrespective of the trip time, we can now determine distribution of the road travel speeds. We redid the analysis by computing all road travel times using this distribution of speeds.

The new set of results are discussed next. As before the feasible vertiport combinations are shown in figure 10. Clearly the feasible region looks very different. We use the aforementioned analysis to re-determine the benefited commuter number and the corresponding vertiport combination. This is shown in table II. The population benefited is almost halved for the commuters with a low value of time case. Roughly 50% of such flexible commuters are benefited with a transfer time of 5 minutes. This number drops to 14% as transfer times increase to 15 minutes. The impact is much more pronounced for commuters with a high value of time as no such commuters benefit when the transfer times are 15 minutes. Even with quick 5 minutes transfers only 33% of commuters benefit from mode shift. A more realistic estimate for commuters with a high value of time is at 10 minutes with about 3% benefiting. Another interesting observation is that the combination of vertiports is now very different. This is potentially due to a more even distribution of demand. This is visible from some test cases, where the total number of vertiports is higher but the overall commuter population supported by the system is smaller.

TABLE II

MAXIMUM NUMBER OF COMMUTERS BENEFITED BY UAM AND THE CORRESPONDING VERTIPORT COMBINATIONS FOR SF BAY AREA WITH LOW CONGESTION ON ROADS. THE NUMBERS IN PARENTHESIS ARE THE VERTIPORT NUMBER COMBINATION (EAST, WEST)

Time Savings % of Trip Time	Transfer Time (minutes)		
	5	10	15
25%	(30,10) 183,012	(20,28) 112,939	(25,29) 47,914
50%	(26,30) 110,791	(29,7) 11,085	(0,0) 0

An important benefit of the analysis in this paper is it provides a visualization of the demand distribution. To demonstrate the spatial distribution, we plotted the distribution of the vertiport clusters over the SF Bay Area for the low congestion case under a time saving of at least 50% and a transfer time of 10 minutes. This is shown in figure 11. Maps like this can support network design research which can then in turn be used for evaluating traffic management strategies or studying air ground interactions resulting from UAM operations. Furthermore, such maps can be augmented with the relative loading of each vertiport as a percent of max capacity. This can inform operational decisions and demand management strategies.

VI. Conclusion

We have developed a traffic demand analysis method to estimate the maximum number of people that can benefit from UAM in a metropolitan region. We studied the use case of commute traffic in San Francisco Bay Area as a sample application of the method. The feasible combinations of vertiports were determined based on capacity constraint and justification of cost of marginal ridership improvement by building additional vertiports. We tested a combination of three cases of vertiport transfer times and two cases of commuter flexibility towards time savings.

Our results specific to the sample use case show that, when roads are highly congested, even at a long transfer time of fifteen minutes and for commuters with high value of time, who only shift with fifty percent or more of travel time savings, around 45% of commuters could benefit from UAM on a travel time basis. We also note that this is under an added constraint on marginal increase in ridership to justify costs. This does not account for other cost considerations such as commuters willingness to pay. On the other hand, with congestion distributed throughout the day with most times being uncongested on the road, a similar magnitude of commuters are benefited only if they have a low value of time and are flexible to move with twenty-five percent time savings, and the transfer times are very short at five minutes. Commuters with a high value of time and fifteen minute transfer time produces no mode shift.

To summarize, our findings indicate that a substantial portion of commuters could benefit based on travel time savings during congested hours of the day and there is a potential for substantial mode-shift to attract public investment. This indicates that UAM has potential to be for the masses instead of just the übermensch. However, since we do not consider the commuter willingness to pay, an assessment of the affordability of UAM as an alternate mode would need further research. Our traffic demand analysis method can be applied to several other similar use cases. The vertiport selection, distribution and the clustering maps produced are useful for evaluating UAM value proposition, policy making and for developing network designs to evaluate air traffic management and demand management strategies and conducting UAM research on related technologies. Our method would also benefit further with the availability of higher fidelity models of vertiport throughput, air traffic control, vertiport operational costs and willingness to pay. These are some of the potential areas of research for future extensions of this work.

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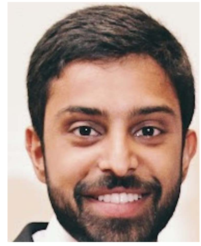

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