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A Top-Down Methodology for Global Urban Air Mobility Demand Estimation

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The convergence of several key technologies during the past decade are enabling the ideation of new Urban Air Mobility (UAM) concepts of operations. UAM systems have the potential to bring significant improvements to the way people move and commute within cities and these include a reduction in commuting time, a reduction of roadway congestion, and a reduction of emissions. Understanding the potential demand for UAM services is crucial for the various stakeholders in order to ensure that the air traffic management systems, the regulations, and the supporting infrastructure are ready and do not slow down the introduction of these services. This paper presents a top-down methodology to estimate the demand for UAM transportation worldwide by estimating the travelers' willingness to pay for UAM services and by estimating the potential volume of UAM traffic. The exercise is implemented as a case study for a set of 31 cities distributed all across the world in 2035.

I. Introduction

NASA defines urban air mobility (UAM) as "a safe and efficient air transportation system where everything from small package delivery drones to passenger-carrying air taxis is operating above populated areas" [1]. Passenger-carrying UAM systems have the potential for numerous societal improvements such as reduced travel time, reduced transportation emissions, and improved accessibility of remote suburbs. Since 1982, roadway congestion has continuously increased due to growth in travel demand exceeding the growth of transportation capacity. This trend has shown no indication of slowing down. In 2017, roadway congestion across urban areas in the United States caused 8.8 billion hours of travel time delays and 3.3 billion gallons of wasted fuel, leading to a congestion cost of $166 billion. Following historical trends of economic growth, transportation system expansion, and adoption of alternate modes of transport, the cost of congestion in the United States (US) is expected to increase to $200 billion by 2025, representing a 20% increase from the 2017 value [2]. The congestion problem is not limited to the US; an analysis of traffic patterns across urban areas globally found the most congested cities to be distributed all across the world with Moscow, Istanbul, Bogota, Mexico City, and São Paulo leading the statistics [3]. Congestion negatively impacts many trip types including everyday commutes, leisure travels, manufacturers relying on on-time deliveries, and companies making scheduled service calls - all of which can inhibit economic growth. Additionally, an environmental cost is paid due to wasted fuel while vehicles are slowed due to traffic. In 2014, transportation systems were the second largest contributors to carbon dioxide (CO_2) emissions globally, accounting for 20% of all CO_2 emissions globally [4]. To address congestion issues and pollutant

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emissions, transportation networks must grow and adopt new technologies at a much faster rate than ever before. The introduction of Urban Air Mobility (UAM) may be a solution to some of these challenges.

As of September 2018, more than 138 manufacturers, investors, operators, suppliers, and governments have invested over $1 billion in UAM technologies and have hopes of competing in a potential near-term multi-billion-dollar market [5, 6]. The realization of a UAM market presents a new form of urban transportation with significant wide-ranging implications. Public planning departments need to be prepared to handle changing traffic patterns as well as be informed about demand to plan the appropriate infrastructure. Air traffic management need to develop appropriate standards and procedures based on the expected volume of air traffic. The industry must understand potential demand to enable data-driven decisions regarding investment priorities. Furthermore, governments must evaluate the environmental impact of potential UAM operations and assess their adequacy with emission reduction targets. Thus, to enable future economic growth, an understanding of the demand for potential UAM operations is paramount.

Market studies conducted by consulting companies such as Horvath and Partners, KPMG, Porsche, and Roland Berger provide context and estimations for the size of UAM operations globally. The estimations provided are however subject to different assumptions and different methodologies. The details of the approach undertaken are not presented in many of the market reports published by these firms, preventing third-party validation of the figures and salient conclusions. A NASA-funded market study conducted by Booz Allen Hamilton (BAH) provides a very detailed methodology but is limited in scope to the United States (US). Booz Allen Hamilton's approach requires data which cannot be found for a large majority of cities worldwide. The approach implements the traditional four-step traffic forecasting model, which may be too complex and difficult to implement for stakeholders across various, diverse industries. For widespread implementation of a demand estimation methodology, the approach and the assumptions made need to be clear and transparent; the approach need to be modular enough to enable higher or lower fidelity analyses as necessary; and the data requirements to execute the methodology must not be prohibitive.

This study seeks to develop a demand estimation methodology which enables global UAM operations estimations and inform the previously mentioned stakeholders. Prior to the development of this methodology, a comprehensive list of demand drivers must be identified, and possible approaches to model them must be evaluated. In addition, since UAM technologies are not yet in service, the barriers to entry must be identified so that the appropriate assumptions can be made. The next section presents a review of available UAM market studies, compiles a list of barriers, investigates promising approaches, and highlights observed demand drivers. Following a literature review, the technical approach section details the proposed methodology and highlights the set of assumptions taken. Finally, an implementation of the proposed methodology is highlighted.

II. Background

For UAM operations to be successful, a number of barriers must first be overcome. Broadly, as defined by a report from Crown Consulting Inc. (CCI), these barriers relate to safety & security, economics, demand, and public acceptance. The complete list of barriers identified by CCI is reproduced in Table 1 [7]. Numerous stakeholders including public planning agencies, regulators, and manufacturers are responsible for tackling these barriers. In order for such stakeholders to be able to properly plan for and make sufficient progress towards UAM viability, stakeholders require knowledge regarding the potential future demand for UAM. For example, the number of flights per day will influence the design and development of a robust air traffic management system. The expected volume of emissions due to electricity drawn from the grid for UAM flights will influence the creation of environmental standards, which could also feedback into vehicle design. The expected fleet size and amount of utilization will influence design requirements for vehicle performance and reliability. As evidenced by the large amount of investments into developing vehicle technology, a high demand for UAM is expected. However, demand estimation has not been widely explored, especially at the global level. The following subsection will explore other demand estimation methodologies to provide a basis for this study.

A. Review of Demand Estimation Methodologies

The field of transportation forecasting has been studied for decades. Traffic forecasts enable public planning agencies to make better decisions regarding the development of roadway and transit infrastructure. The most widely used forecasting methodology is the Four-Step Transportation Model, visualized in Figure 1. The process begins by first dividing the region of study into discrete traffic analysis zones. Then for each zone, land use and socioeconomic data is identified. Based on these demographics, the number of trips produced (origin) and attracted (destination) by each zone is determined. The trip distribution step matches trip origins to trip destinations to create actual trips, typically

Table 1 A compiled list of barriers to entry along with scenarios enabling viability [7, 8]

Category	Barriers to a Viable UAM Market	Critical Events or Tipping Points Indicating Viability
Safety and Security	Detect-and-avoid capability GPS-denied technology Weather mitigation Unmanned Traffic Management (UTM) Regulatory requirements UTM certification Flight above people Weight and altitude restrictions Beyond visual line of sight Operator certification Environmental restrictions Emergency procedures Data security	Comprehensive regulatory climate in place UTM technology matured Cybersecurity standards established
Economics	Battery technology Vehicle performance and reliability Autonomous flight technology Electric propulsion efficiency Vertiport/Vertistop Infrastructure	Annual reduction in cost per trip Introduction of autonomous operations Initial investments in infrastructure Annual growth of infrastructure
Demand	Competing modes (train, bus, bike, ride-share)	Annual growth in number of urban passenger trips Annual growth in air market share as percent of all urban passenger trips
Public Acceptance	Proven safety record Pilot training Privacy Job security Environmental threats Noise and visual disruption	Proven safety record better than ground mode travel Number and severity of local operational restrictions

through a gravity model. Each trip is then assigned to a specific mode of transportation, typically through a random utility discrete choice model. In the fourth step, the trips are assigned to specific segments in the network. Network characteristics are re-calculated and the four steps are iterated until demanded trips match route capacity. At this point, the total volume of traffic by trip purpose, trip mode, and route is identified [9].

The Four-Step Model requires detailed demographics data, calibrated equations and models capable of estimating trip counts and modal splits, a gravity model with calibrated friction factors, and a representative transport network. Acquiring the required data-sets (assuming availability) and developing the necessary models capable of analyzing any global city prevent the adoption of this widely used methodology. The Four-Step Model can however serve as a road-map for developing a new approach.

A core goal of the desired methodology is to perform demand estimation of any global city and for a potentially large set of cities. Thus, the desired methodology should be capable of considering attributes of a city which can be reasonably estimated or assumed. First, the Trip Generation and Trip Distribution steps are investigated. Performing an origin-destination (O/D) level analysis is not feasible for two reasons: it is too computationally expensive, and the data

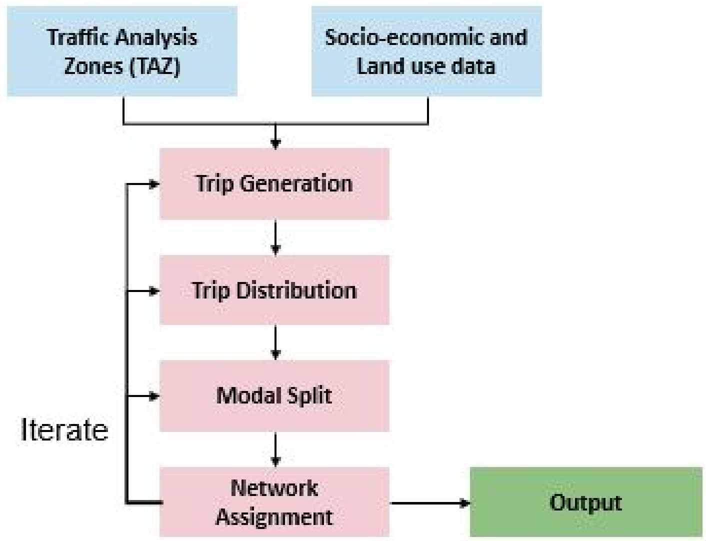

Fig. 1 Traditional Four-Step Transportation Forecasting Model [10]

needed to support analysis at this level is prohibitive. The goal of these two steps is to identify specific trips and their attributes to feed the mode split model, which is responsible for assigning the trips to different modes of transportation. Trip data and relevant attributes aggregated at the city level are publicly available in the United States through the US Department of Transportation; similar data however is much more limited globally. Nonetheless, commercial vendors like INRIX and TomTom source and aggregate traffic data across global markets. The specific type of traffic data required will be identified and specified in the Technical Approach section.

Next, we move to the modal split step. Modeling consumer behavior is an entire field of study on its own, and extensive studies have been conducted. The Four-Step Model typically employs some type of utility discrete choice model, which attempts to use trip attributes such as trip cost, trip time, convenience, comfort, wait time, etc. and traveler attributes such as income, sex, age, race, etc. to predict mode choice behavior. These models are typically calibrated using either revealed preference (RP) or stated preference (SP) data. Revealed preference data describes historic traffic data, while stated preference data is derived from surveys. Due to the absence of an existing transportation option comparable to UAM, outside of niche markets, a revealed preference approach is not possible. Conducting a survey to estimate the preferences of any traveler in any city is also not feasible and is outside of the scope of this study. Instead, an approach considering the inherent benefits of UAM without the need for traveler behavior data is sought.

The primary benefit and the core business case of UAM is the time savings achieved through a UAM trip instead of a conventional mode of transport. Therefore, the decision a traveler makes regarding which mode choice to use for a trip can be considered as a function of the value that traveler places on their time saved. By estimating the value of time, a traveler's willingness to pay (WTP) for a trip through a specific mode of transport can be calculated. A binary choice model described by Sirirojvisuth, Briceno, and Justin suggests that if the WTP of a traveler for a UAM trip is greater than the cost of the UAM trip, then the traveler will choose UAM as their mode choice [11]. The WTP is estimated as the total value of time saved during a trip plus the cost of an alternate mode of transport, as detailed in Equation 1. The value of travel time savings (VTTS) is the value per unit time, as a function of the income of the traveler and trip purpose. Typically, VTTS ranges between 35% and 60% of earnings per unit time for personal trips and between 80% and 120% for business trips [11]. The primary benefit of this approach is that it does not require calibration using RP nor SP data-sets, and therefore can be applied to a large scope of cities.

$$WTP = VTTS(income, purpose) * Trip\ Time\ Saved + Trip\ Cost\ of\ Alternate\ Mode \tag{1}$$

The last step of the Four-Step Model is assigning trips to a network model. This step may be used to identify congested routes and develop plans for specific infrastructure development. However, since an O/D-level analysis is prohibitive, this step provides no added benefit to the demand estimation process.

In summary, implementing the conventional Four-Step Traffic Model is found to be infeasible for the goals of this methodology. Instead, the model was used as a starting point to find alternative methods that can still estimate demand at a large scale and scope. The next section will discuss the derived methodology and provide more insight into the data requirements and assumptions involved.

III. Technical Approach

Similar to previous studies, the derived methodology utilizes a top-down approach to estimate UAM operations. Three descriptors have been identified to quantify UAM operations: passenger demand, flight hours, and fleet size. Each of these three descriptors can be broken down as a function of UAM traffic, in terms of passenger kilometers (PKM) traveled. Thus, the primary goal of this methodology is to estimate UAM PKM.

In terms of a top down approach, UAM PKM can be estimated to be some percentage of the total addressable market, which shall be represented as the total ground-based passenger traffic occurring within a city. The share of this total PKM which will be addressed by UAM is the percentage of the population that will choose to use UAM as the mode of transport for a given trip instead of conventional ground-based transport. Later subsections will describe how each component of the top-down approach is be calculated.

A. Near-Term Assumptions

First, a set of guiding assumptions are established. For UAM operations to be realized, several technological advancements must occur in the near term (2020 – 2035). This methodology assumes that key technology trends regarding improvements in battery technology, propulsive efficiency, and noise will continue. Regulations and certification standards will develop and accommodate UAM operations. A strong safety record will be built, and there will be high societal acceptance. Vertiport infrastructure will develop and a network will exist which is sufficient to support economical UAM operations. The methodology will focus on estimating operations for the 2035 – 2050 time-frame. Other assumptions will be made clear as each part of the methodology is described.

B. UAM Market Share Estimation

As described in the previous section, evaluating the willingness to pay (WTP) for UAM operations of a traveler to estimate their mode choice decision is a valid and favorable approach. WTP is a function of the value of travel time savings (VTTS) an individual may place per unit time saved, the time savings of using UAM instead of an alternate mode, and the cost of a trip using the alternate mode. VTTS may be represented as a function of income level and trip purpose. The following equation describes the necessary condition for an individual to use UAM instead of an alternate mode of transport. By evaluating this function across the entire range of values for distance, income, and trip purpose, the set that enables UAM travel is identifiable.

$$Cost_{UAM}(d) \leq WTP = Cost_m(d) + VTTS(income, purpose) * (Time_m(d) - Time_{UAM}(d)) \tag{2}$$

$Cost_{UAM}(d)$ is the cost of a trip of distance d using UAM as the mode of travel. The cost model function for UAM trips is complex and developing this model is out of the scope of this study. Instead, this function shall be parameterized, which also enables the generation of various scenarios. Guidance may be sought through other market forecasts which have developed supply models to estimate trip costs. It is expected that his function will take on a direct linear behavior with respect to distance within a specific economic range. Outside of this range, the cost will be prohibitively high to operate.

$Cost_m(d)$ is the cost of a trip of distance d using mode m as the mode of travel. The cost for mode m, which can be personal vehicles or public transit, can be identified for most cities through public information. For example, AAA found through a study in 2014 that the average cost for operating a new personal sedan in the US is 59.2 cents per mile; this figure considers costs of ownership such as sale price, depreciation, maintenance, repair, and fuel. Similarly, public transit costs can be identified on a city-by-city basis.

$VTTS(income, purpose)$ is the value an individual of a specific income traveling for business or personal would place on each unit time saved. As mentioned previously, VTTS typically ranges between 35% and 60% of earnings per unit time for personal trips and between 80% and 120% for business trips [12].

$Time_m(d)$ is the trip time for a trip of distance d using mode m. The trip time for each mode (personal vehicle and public transit) is estimated as a function of distance by using either an assumed average speed or a speed curve which varies with distance. Considering time of day impacts due to rush hour vs. free flow traffic is expected to add significant complexity and will not be pursued in this methodology. Instead, average speeds across the entire day will be considered. To estimate average trip speeds for ground vehicles, isochrone maps or google maps data can be leveraged. A regression model can be fit to this data to enable computational analysis.

$Time_{UAM}(d)$ is the trip time for a trip of distance d using mode UAM. The total trip time for a trip involving UAM is a complicated non-linear function. It is now necessary to identify that the UAM mode choice is actually a multi-modal choice. The traveler will need to arrive at a vertiport location to board a UAM vehicle and arrive at the final destination after deboarding the UAM vehicle. The modeling of UAM trip time is dependent on the concept of operations (CONOPS) which includes trip time to arrive at a vertiport, time to load passengers into the vehicle, the actual UAM flight time, de-boarding time, and time to reach final destination. The UAM flight segment will be easy to estimate, by using an assumed average vehicle ground speed. For all other segments, functions or fixed time values shall be assigned based on desired complexity and fidelity. For example, a simple option is to estimate 10 minutes to arrive to a vertiport, 5 minutes to board, 2 minutes to deboard, and 10 minutes to arrive at the final destination. A more complex option is to replace the times to arrive at the vertiport and final destinations with trip time functions of alternate modes. Additionally, as infrastructure density increases and operational efficiencies are achieved over time, the times for each segment in the CONOPS will gradually decrease. The specific implementation is left up to the researcher.

Once all subfunctions are developed and compiled, a complete space of trip distance, traveler income level, trip purpose, and travel mode are evaluated. A notional point evaluation is shown.

Inputs:

- Trip distance, d = 30 km
- Alternate mode, m = public transit
- Annual income of traveler = $100,000
- Trip purpose = business

Function Evaluation:

- Cost of trip by UAM = $30
- Cost of trip by public transit = $5
- VTTS($100k, business) = $1/min
- Trip time by public transit = 60 min
- Trip time by UAM = 20 min

Through this notional evaluation, it is found that a time savings of 40 minutes results in a value of $40. Combined with the cost of a public transit ticket of $5, the total willingness to pay of this individual for UAM is $45. The cost of a UAM trip for 30 km is stated to be $30. Thus, the individual will choose to use UAM.

Similarly, a complete evaluation of the space must be conducted to identify the subset of the space which will be addressed by UAM. Once this subset has been identified, the distribution of total traffic across all ground transport must be overlaid to identify expected UAM PKM.

C. Total Addressable Market

Based on the method for finding UAM market share, the total PKM will need to be identified as a function of distance, income, purpose, and mode. Unfortunately, traffic volume dis-aggregated by each of these attributes will be difficult to find for cities outside of the United States. A brief search of public and commercial data has found that the following types of data are available for many markets:

- Total PKM across all ground modes at the city level
- Trip distance distribution for passenger vehicles at the city level
- Modal split of trips taken at the city level
- Share of trips by purpose at the country level
- Household income distribution at the country level

To bring together these data-sets, each set is assumed to be independent of the other; trip distribution, modal split, trip purpose share, and income distribution do not vary with respect to each other. Public transit trip distance distribution follows the same distribution as passenger vehicles. Modal split by number of trips is the same as modal split by PKM.

Through these assumptions, the total PKM associated with a specific viable range of input variables is calculated as described in Equation 3, where s_m is the share of trips associated with mode m, s_p is the share of trips associated with purpose p, CDF_{TD} is the cumulative distribution function (CDF) of trip distance, and CDF_{inc} is the CDF of household income.

$$PKM_{UAM} = PKM_{tot} * s_m * s_p * (CDF_{TD}(d_2) - CDF_{TD}(d_1)) * (CDF_{inc}(inc_2) - CDF_{inc}(inc_1)) \quad (3)$$

D. Addressing Data Acquisition Challenges

Acquiring or generating the data mentioned in the previous two subsections is a significant challenge for the implementation of this methodology. Regarding a global scope of cities, issues arise with data availability, budget constraints, or processing and resources constraints. In the event of partially constructed data-sets, the researcher has two options to complete the data-set. The easier and more reliable option is to build a regression model using the available data to estimate data gaps. The regression model will need to be a function of other correlated data available. In the event that a regression model cannot be fit, a clustering approach may be taken to group cities of similar characteristics together. All cities within the same cluster can be assumed to have similar values for the missing data, and appropriate assumptions can be made to fill the cities' data gaps. The clustering activity must be performed based on an alternate set of attributes which are representative of those that are missing, i.e. a proxy data-set. Table 2 identifies potential proxy data for each of the attributes mentioned in the previous two subsections.

Table 2 A list of all data requirements and potential proxy data to enable the filling of data gaps.

Data	Proxy Data for Regression or Clustering Models
Travel cost as a function of transport mode and distance	Quality of roads, metro network length, GDP/capita
Household income distribution or average	GDP/capita
Average travel speed as a function of transport mode	Congestion, population density
PK distribution as a function of distance	Metro network length, land area, pop. density
Public transit PK, as a % of total PKM	Metro network length
Trip purpose, as a % of total PKM	Global Competitive Index

Multiple clustering techniques are available for potential implementation; however, review of clustering theory is not within the scope of this paper. During implementation of this methodology, the researcher is recommended to examine the distribution of data which must be clustered and identify the most appropriate option.

IV. Implementation

The methodology presented has been implemented for a set of 31 cities in the year 2035 to display the methodology's capabilities. The chosen 31 cities were cited in a market report by KPMG as being likely to observe UAM operations in the near-term [13]. These 31 cities are reproduced in Table 3.

Table 3 Scope of cities identified for implementation

Tokyo	Shanghai	New York
Beijing	Seoul	Los Angeles
Osaka	Guangzhou	Tianjin
Mexico City	Shenzhen	Sao Paulo
London	Paris	Chicago
Bangkok	Jakarta	Wuhan
Kuala Lumpur	Dallas	Hong Kong
Toronto	Madrid	Houston
San Francisco	Melbourne	Sydney
Washington DC	Phoenix	Taipei
Dubai		

A. Data and Assumptions

Demand forecasts and estimates are highly dependent on the assumptions made to generate them. In the technical approach section, the methodology and its assumptions are detailed. In this section, the assumptions taken to generate the required data are discussed.

1. Concept of Operations

First, it is necessary to define the concept of operations (CONOPS) for this implementation. A ride-share option is used to arrive at a vertiport, defined as the access trip. Once at the vertiport, the traveler boards the air taxi and completes security checks. The flight occurs at a constant cruise speed of 240 km/hr and will conservatively follow the entire ground trip distance. At the destination vertiport, the traveler deboards, exits the station, and uses a second ride-share option to reach their final destination, defined as the egress trip. The access and egress trip distances are calculated as a function of vertiport network density. By assuming a grid-like distribution of vertiports, an average access and egress distance is taken as 2/3 of the maximum distance to a vertiport. As a baseline, one vertiport every 300 sq. km is assumed, equating to roughly 6 vertiports within a city the size of London. This CONOPS is shown in Figure 2.

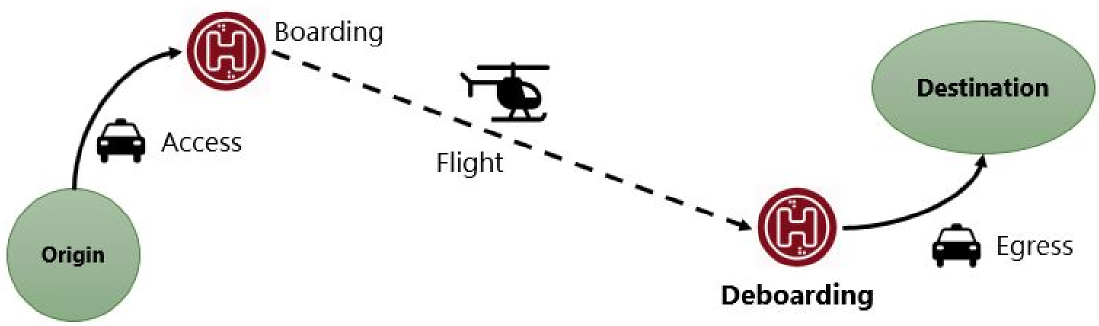

Fig. 2 Concept of Operations (CONOPS)

2. UAM Ticket Cost

The UAM trip cost is defined in Equation 4. The ride-share costs for access and egress assume \$2/mi in the US, and are adjusted according to cost of living (COL) across all other markets. COL indices are sourced from WorldData.info [14]. The cost for a UAM flight is more difficult to estimate since there is no historical data. Some market reports have developed cost models, and have reported a wide range of possible ticket costs. Uber estimates VTOL prices to start at \$2.09/pax-mi (\$1.30/pax-km) during initial operations and decrease to \$0.69/pax-mi (\$0.43/pax-km) over the near-term [8]. Crown Consulting Inc. reported an average cost of \$1.50/pax-mi (\$0.93/pax-km) in 2030 [7]. Booz Allen Hamilton reported prices between \$11.00/pax-mi (\$6.84/pax-km) for a 2-seat VTOL and \$6.25/pax-mi (\$3.88/pax-km) for a 5-seat VTOL in the near-term. For reference, current helicopter operators like Blade and Skyride charge roughly \$20/pax-km and Voom charges roughly \$5/pax-km [6].

To consider this wide range of possible UAM ticket costs, multiple points will be sampled. Based on these reports, we expect the costs to be between \$0.30 - \$3.60 per passenger-km, by 2035. Therefore, we sample this range at steps of \$0.30/pax-km. To evaluate an upper-bound, \$7.20/pax-km will also be evaluated. The selected costs will be representative of a US market, and the COL index will be applied to adjust the ticket cost for all other markets. Booz Allen Hamilton's report found that roughly 55% of costs for a 4-seat eVTOL are made up by indirect operating costs, infrastructure cost, crew costs, route cost, profit structure, and taxes, while the remaining 45% is made up by capital cost, insurance cost, battery reserve, maintenance, and energy costs. This approach assumes only the first group of costs (indirect operating costs, infrastructure cost, etc.) may be adjusted by cost of living, while the remaining costs will be fixed across all markets. For simplicity, 50% of the UAM ticket cost respective to the US will be adjusted by COL across other markets.

$$Cost_{UAM} = Cost_{access} + Cost_{flight} + Cost_{egress} \tag{4}$$

3. *Cost of Alternate Modes*

Costs for all alternate modes will operate under *current market conditions*. The current cost of operating a personal vehicle in the US is assumed to be \$0.59/mi (\$0.37/km), as estimated by AAA [15]. The cost of an intra-city public transit ticket (metro) in the US is assumed to be \$2.50/trip. The cost for a inter-city public transit ticket is assumed to be \$20/trip, where an inter-city trip is defined as a trip with trip distance exceeding the radius of the city. Further, some sort of public transit mode for intra- and inter-city is assumed to be available for all cities. The costs of trips for all cities outside of the US is again found by applying a COL adjustment. The radius of each city is based on land area, which is sourced from Demographia World Urban Areas (2019) [16].

4. *Value of Travel Time Savings (VTTS)*

VTTS is assumed to be 50% of earnings per unit time for all personal trips and 100% for all business trips, based on guidance from the US Department of Transportation [12].

5. *Travel Time of Alternate Modes*

The travel time of a trip using an alternate mode is found by estimating the average speed of the trip. Speed of a trip is generally a function of trip distance; shorter trip distances see slower average speeds while longer trip distances see faster average speeds. To model this relationship, several random points of varying trip distances are sampled across each of the 31 cities. A logarithmic model, described in Equation 5 is used to fit the sampled data. Figure 3 shows a sample fit of passenger vehicle trip speeds in Paris, France; the data points were collected by the authors by selecting the city center as the origin and several randomly selected locations at different distances.

$$Speed_m(d) = a_m * ln(d) - b_m \tag{5}$$

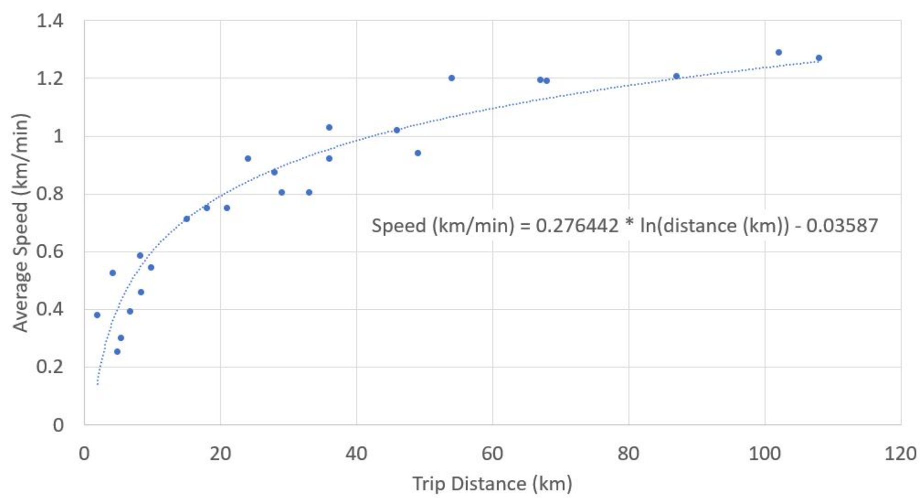

Fig. 3 Logarithmic fit to randomly sampled routes in Paris using passenger vehicle

6. *UAM Trip Time*

The UAM trip time is defined in Equation 6. The access and egress times are calculated using the personal vehicle speed curve of the associated city and the average access and egress times described in the CONOPS subsection. Boarding time is assumed to be 5 minutes, and it covers the time to enter the vertiport, board the air taxi, and complete safety checks. De-boarding time is assumed to be 2 minutes, and it covers the time to de-board the air taxi and exit the vertiport. Lastly, flight time is calculated using a constant cruise speed conservatively following the entire ground trip distance. A study by Uber suggests desirable VTOL speeds will likely be between 150 mph and 230 mph, where the optimal speed is a trade-off between propulsive efficiency and vehicle productivity to amortize costs. Due to uncertainty in future vehicle speeds, this implementation will conservatively assume a constant cruise speed of 150 mph, or roughly 240 kmh [8].

$$Time_{UAM} = t_{access} + t_{board} + t_{flight} + t_{deboard} + t_{egress} \quad (6)$$

7. Total Ground PKM

Total PKM data was sourced at the country level for Australia, China, Spain, France, Great Britain, South Korea, Mexico, and US using statistics from the ITF Transport Outlook (2019), which is reproduced in Figure 4 [17]. The total PKM is divided by the country population to find PKM per capita, and a linear regression was then built between GDP/capita and PKM/capita to fill data gaps for PKM not represented in ITF's outlook [18]. The regression, which has an r^2 value of 0.925, is shown in Figure 5. Then, UN's urban population forecast was used to estimate the population of each city in 2035 [19]. Lastly, the 2035 population was multiplied by the PKM/capita to find total PKM in each city in 2035.

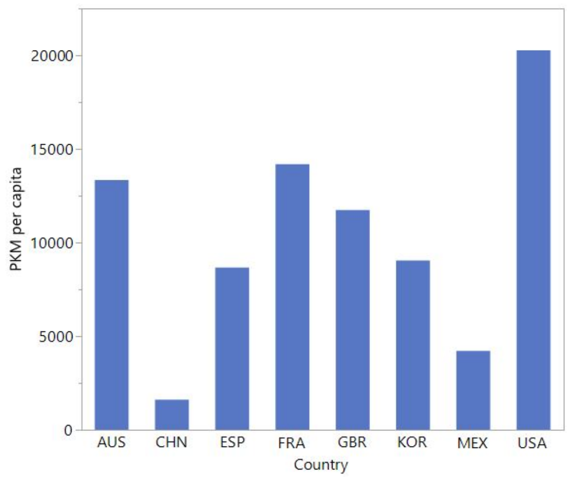

Fig. 4 Total passenger kilometers traveled by country

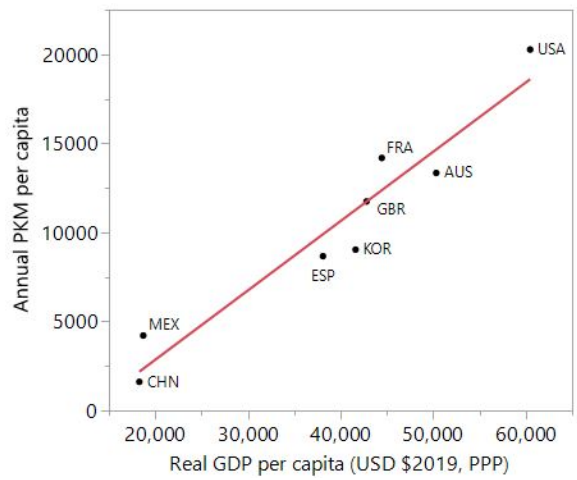

Fig. 5 Passenger kilometers traveled per capita vs. GDP per capita

8. Modal Split

Modal split data is acquired from a reference developed by Singapore's Land Transport Authority (LTA) Academy [20]. The resource compiles mode shares as reported by local governments across global cities. The modal splits typically contain private transport, rail, bus, taxi, cycle, walk, and other. Since cycling and walking trips are typically for very small distances, these modes are omitted, and new mode shares are calculated. 'Other' is also omitted. Taxi is grouped with private transport, and bus and rail options are grouped with public transit. Figure 6 shows a sample mode split reference for Beijing. For this case, the re-calculated modal splits for private transport and public transit are 47% and 53% respectively.

9. Purpose Split

Due to project limitations, significant effort was not placed on gathering purpose split data. A study on national travel statistics in Europe by the EU Joint Research Committee found roughly 5% of trips conducted in select countries were traveled for business purposes. For this implementation, a purpose split of 5% for business and 95% for personal is assumed for all cities.

10. Trip Distance Distribution

Trip distance distribution data is available through a commercial source, INRIX, for a majority of the cities within the scope. However, due to budget constraints, data for a maximum of five select cities could be acquired. The researchers choose to implement a clustering approach to group similar cities together, and source traffic data for only representative cities. The distribution of trip distances within a city is expected to be related to land area, population density, and

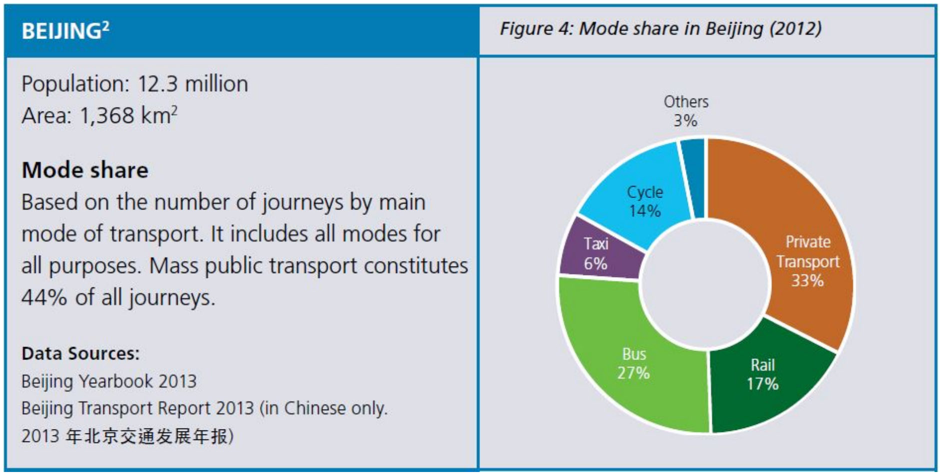

Fig. 6 Mode share in Beijing as compiled by LTA [20]

metro network density. A k-means clustering approach with $k = 5$ is used to perform the clustering activity. The results are shown in Table 4, and qualitative descriptions of each cluster is shown in Table 5. Clusters 1, 2, and 5 all have similar metro network density and primarily differ in land area and population density. Cluster 1 contains cities with mid to low land areas and relatively low population densities; cluster 2 contains cities with high population densities and low land areas; and cluster 5 contains cities with low population densities but significantly higher land area. Cluster 3, which only contains Hong Kong, is an outlier due to its very high relative population density and metro network density. Lastly, cluster 4 contains cities with similar land areas and population densities as clusters 1, 2, and 5, but has a higher metro network density.

Within each cluster, the city closest to the centroid of the cluster was chosen as a representative city, and the relevant data is acquired. The chosen representative cities are Paris, Mexico City, Hong Kong, London, and New York. Trips data for Paris, Mexico City, and London is purchased from INRIX [21]. Trips data for New York is publicly available through the National Household Travel Survey (2017) [22]. Trips data for Hong Kong is not available publicly or commercially, and so it is linked to cluster 4 on the basis of closest similarity to metro network density.

Lastly, a log-normal distribution is fit to each of the traffic data-sets acquired, and the distribution is applied to every city within a cluster. Figure 7 shows a sample distribution from Mexico City and the associated log-normal fit.

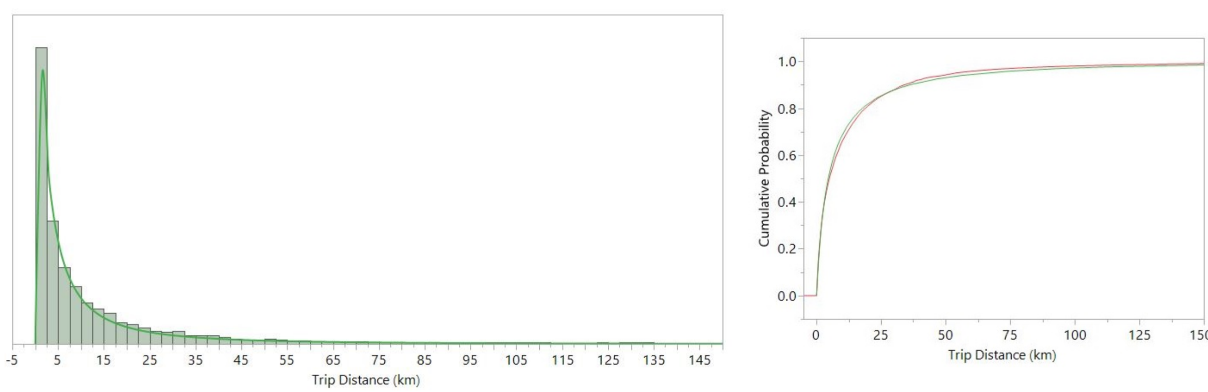

Fig. 7 Trip distance probability density function (left) and cumulative distribution function (right) for Mexico City, data provided by INRIX [21]

11. Household Income Distribution

City level income distribution data was not easily accessible for all cities within the scope of implementation. Therefore, the city level distribution is assumed to be the same as the country level distribution; country level income

Table 4 Cities clustered using k-means algorithm across land area, population density, and metro network density to find representative cities for acquisition of trips data

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Shanghai	Jakarta	Hong Kong	London	Tokyo
Guangzhou	Seoul		Wuhan	New York
Beijing	Sao Paulo		Madrid	
Los Angeles	Mexico City		Sydney	
Paris	Osaka			
Chicago	Bangkok			
Kuala Lumpur	Shenzhen			
Washington	Tianjin			
Toronto	Taipei			
Dallas				
Houston				
San Francisco				
Phoenix				
Melbourne				
Dubai				

Table 5 Qualitative cluster characteristics

City Cluster	1	2	3	4	5
Metro Network Density	Middle	Middle	Very high	High	Middle
Land Area	Mid-low	Low	Very low	Low	High
Population Density	Low	High	Very high	Middle	Low

data is sourced from World Bank's PovcalNet tool. The income is then forecast to 2035 by assuming an average annual inflation rate, by country. Average annual inflation rate is sourced from PWC's Global Economic Projections, which provides forecasts across 2022-2026; inflation rate forecasts until 2035 were not available [23]. Additionally, some regions are not available on PWC's forecasts; for these regions, a 20-year historical average from the IMF World Economic Outlook is used [24]. To further enable computational analysis, a log-normal distribution is fit to each data-set. A sample distribution and model-fit are shown in Figure 8 [25].

B. Results

Tables 6-9 show the results of this implementation, considering the 31 cities mentioned in Table 3 during 2035. UAM ticket cost and vertiport density are primary demand drivers for UAM operations. UAM ticket cost is the basis of the willingness-to-pay function, which designates which trips are viable for UAM operations. Vertiport density controls the spacing between vertiports and thus impacts the travel time and cost involved in arriving to the origin vertiport and reaching the final destination from the destination vertiport. Therefore, A range of UAM ticket costs and vertiport densities are evaluated.

Tables 7-9 are derived from the total UAM PKM, show in in Table 6. The results show that there is significant demand for UAM travel across a wide range of ticket costs and infrastructure developments. As detailed in these tables and visualized in Figures 9-11, UAM demand has a near-logarithmic behavior with each variable. At costs less than $0.90/pax-km, demand begins to grow at a rate faster than exponential growth. This trend is expected, as such low-price points become cheaper than rideshare services and personal vehicle ownership. Thus, if manufacturers are able to achieve low-price points and cities are able to develop the necessary infrastructure, there will be significant demand for UAM. However, a supply side analysis is needed to understand what amount of demand can be met.

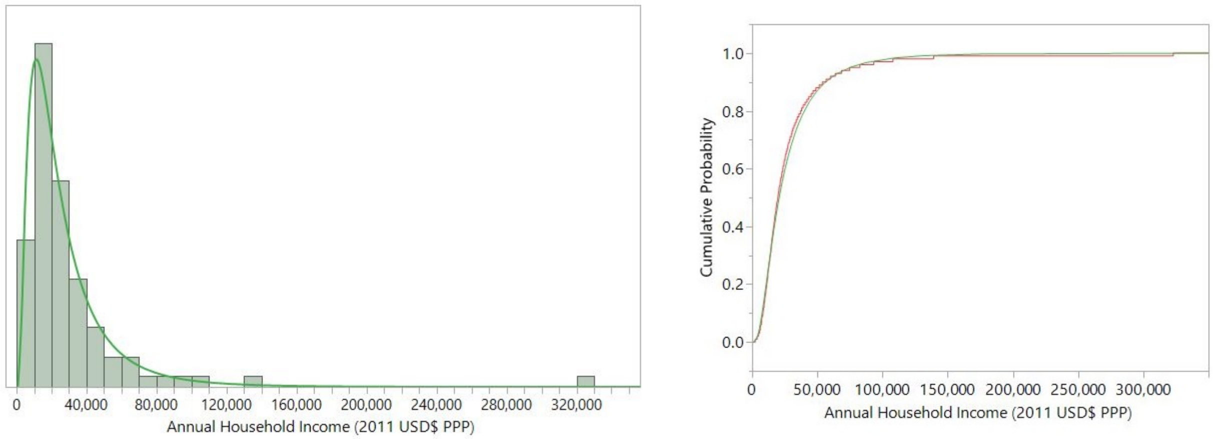

Fig. 8 Income probability density function (left) and cumulative distribution function (right) for Mexico in 2035 [25]

A UAM market report by CCI provides the closest point of comparison for demand estimates across all available market reports based on its scope and description of assumptions. CCI considered 15 of the largest cities in the US, and generated an estimate of 740 million passenger trips in 2030 at a UAM ticket cost of about $0.93/pax-km. At a similar price point, our implementation found 1,207 to 327 million passenger trips across 31 global cities in 2035. This comparison offers some validation, but it should be reiterated that demand estimates are highly sensitive to the assumptions made, and comparisons are difficult to validate when all assumptions are not known.

Table 6 Annual UAM passenger kilometers

Annual UAM PKM (Million)				
		Vertiport Density (area, km², per vertiport)		
		150	300	450
UAM Ticket Cost ($/km)	$ 0.30	361,240	201,287	136,167
	$ 0.60	111,360	65,349	45,071
	$ 0.90	53,985	32,030	22,481
	$ 1.20	30,670	17,909	12,798
	$ 1.50	18,365	10,769	7,632
	$ 1.80	11,716	6,984	4,971
	$ 2.10	8,007	4,529	3,247
	$ 2.40	5,395	3,101	2,193
	$ 2.70	3,732	2,186	1,567
	$ 3.00	2,794	1,548	1,109
	$ 3.30	1,988	1,094	810
	$ 3.60	1,448	843	584
	$ 7.20	83	45	31

Table 7 UAM share of total ground PKM

UAM Share of Total PKM				
		Vertiport Density (area, km², per vertiport)		
		150	300	450
UAM Ticket Cost ($/km)	$ 0.30	8.507%	4.740%	3.207%
	$ 0.60	2.623%	1.539%	1.061%
	$ 0.90	1.271%	0.754%	0.529%
	$ 1.20	0.722%	0.422%	0.301%
	$ 1.50	0.433%	0.254%	0.180%
	$ 1.80	0.276%	0.164%	0.117%
	$ 2.10	0.189%	0.107%	0.076%
	$ 2.40	0.127%	0.073%	0.052%
	$ 2.70	0.088%	0.051%	0.037%
	$ 3.00	0.066%	0.036%	0.026%
	$ 3.30	0.047%	0.026%	0.019%
	$ 3.60	0.034%	0.020%	0.014%
	$ 7.20	0.002%	0.001%	0.001%

Table 8 Annual UAM passenger trips

Annual UAM Pax Trips (Million)				
		Vertiport Density (area, km², per vertiport)		
		150	300	450
UAM Ticket Cost ($/km)	$ 0.30	6,355	2,645	1,607
	$ 0.60	2,313	1,065	635
	$ 0.90	1,207	541	327
	$ 1.20	708	306	185
	$ 1.50	437	182	112
	$ 1.80	287	119	71
	$ 2.10	196	77	47
	$ 2.40	131	52	31
	$ 2.70	94	36	22
	$ 3.00	69	26	16
	$ 3.30	49	18	12
	$ 3.60	37	14	8
	$ 7.20	2.1	0.7	0.4

Table 9 Annual UAM utilization

Annual UAM Utilization (Million hrs)				
		Vertiport Density (area, km², per vertiport)		
		150	300	450
UAM Ticket Cost ($/km)	$ 0.30	1,505	839	567
	$ 0.60	464	272	188
	$ 0.90	225	133	94
	$ 1.20	128	75	53
	$ 1.50	77	45	32
	$ 1.80	49	29	21
	$ 2.10	33	19	14
	$ 2.40	22	13	9
	$ 2.70	16	9	7
	$ 3.00	12	6	5
	$ 3.30	8	5	3
	$ 3.60	6	4	2
	$ 7.20	0.3	0.2	0.1

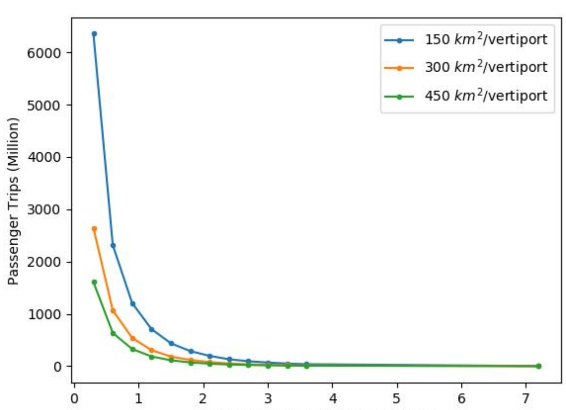

Fig. 9 Annual UAM Passenger Trips vs UAM Ticket Cost

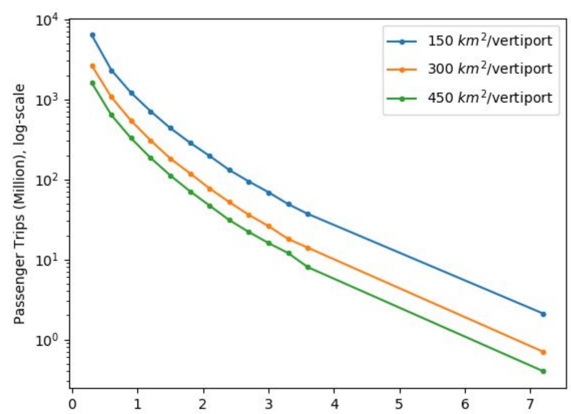

Fig. 10 Annual UAM Passenger Trips vs UAM Ticket Cost, log-scale

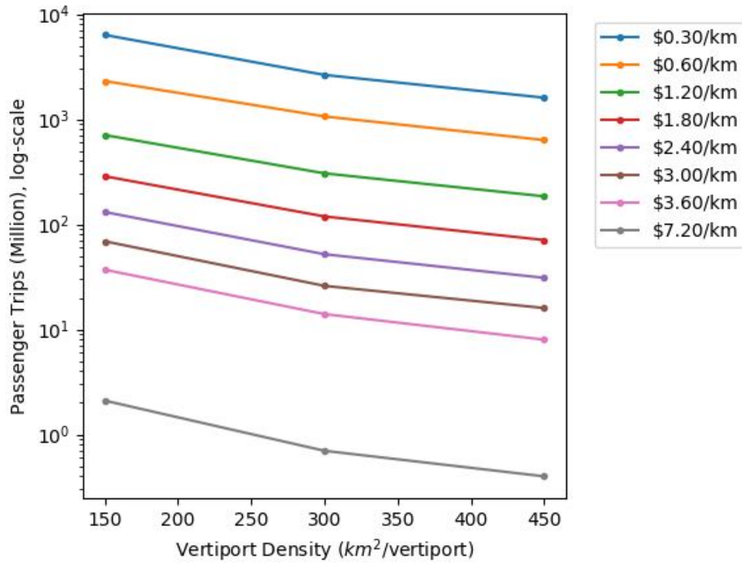

Fig. 11 Annual UAM Passenger Trips vs Vertiport Density, log-scale

V. Conclusion

This paper presented a methodology to forecast demand for Urban Air Mobility (UAM) operations applicable to any global city with fewer data requirements than traditional demand forecasting methodologies. The presented methodology generally follows a top-down forecasting approach and has two primary components. First, the set of trips viable for UAM travel are identified by comparing the willingness to pay (WTP) of travelers for UAM trips with the cost of a UAM trip. The binary model assumes that all trips with a higher WTP than the UAM trip cost will choose UAM as the mode choice. Second, each trip identified as a UAM trip is evaluated to estimate the total volume of ground traffic, in passenger-kilometers (PKM), which is traveled across the associated trip parameters. Evaluated trip parameters include trip purpose, trip distance, traveler income, and alternate mode. Lastly, by summing the volume of traffic across all viable trips, the annual traffic volume is estimated. Additionally, descriptors such as passenger trips and utilization are derived.

The methodology is implemented for a set of 31 large cities which are expected to see UAM operations in the near-term. The implementation estimated demand forecasts for 2035 and found indications of strong market demand for a range of UAM ticket costs and vertiport infrastructure developments. Additionally, the results show a near-logarithmic relationship between demand and both UAM ticket cost and vertiport density. Therefore, if manufacturers and city planners can work together to drive costs down and continually develop and expand vertiport infrastructure, exponentially larger numbers of travelers will demand UAM travel. Manufacturers may leverage these results to identify and plan for an optimal production rate, as achieving cost reductions is related to the number of vehicles produced. City planners will seek to couple this information with a supply side analysis to see how much demand can physically be met and create plans for infrastructure development. By 2035, air traffic management systems in cities should have the capability to handle tens of thousands of passengers per day. Regulators must move quickly to outline vehicle certifications and flying regulations to enable manufacturers and cities to begin developing these capabilities. In summary, multiple stakeholders must come together to enable Urban Air Mobility. Their efforts to reduce cost and develop infrastructure will be met with significant demand.

VI. Future Work

This study is an ongoing effort aimed at generating global demand estimates for 500 of the top global cities between 2035 and 2050. The results presented in this paper for the small scope of 31 cities will next be further evaluated to assess the accuracy of the assumptions made by conducting a city by city validation. Key assumptions such as transforming costs based on cost of living of different markets, assuming current market conditions, approaches for filling data gaps, and more will be re-visited and evaluated. Following the development of more accurate assumptions, a large-scale implementation will be performed.

Outside of the scope of this study, other improvements can be made. The WTP function currently only considers quantitative choice attributes; a novel approach to incorporate qualitative attributes such as comfort, convenience, or perception of wait times without the need to calibrate against historical or survey-based data would be highly valuable. A rudimentary origin-destination level analysis based on high-level city data such as land area and population distribution (achievable through isochrone maps, for example) would be valuable to better place vertiports and estimate trip times for UAM and alternate modes. Similarly, many other aspects can be modified to incorporate a higher-fidelity analysis due to the modular nature of the methodology.

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Clean Sky 2

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