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A Scenario-Based Evaluation of Global Urban Air Mobility Demand

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Urban Air Mobility (UAM) is an emerging aviation market with the capability to offer dramatic societal improvements to the way people move and commute in urban areas, including reductions in commuting time, emissions, and traffic accidents. An understanding of the potential demand for UAM services is crucial for stakeholders to ensure that the supporting infrastructure is ready and does not hinder the introduction of these services. In a previous study, the authors developed a top-down methodology for evaluating the demand for global UAM networks by estimating the travelers' willingness to pay for services and estimating the potential volume of UAM traffic. The methodology was implemented in that study for a subset of 31 cities distributed across the world in 2035. This paper seeks to expand the scope of the previous study to quantify global UAM demand for 542 of the top global cities in an extended time frame from 2035 up to 2050. Additionally, this study employs a scenario-based forecasting approach to capture long-term market demand based on low and high penetration levels for UAM services.

I. Nomenclature

AAA	=	American Automobile Association
CCC	=	Cubic Clustering Criterion
CoL	=	Cost of Living
$CONOPS$	=	Concept of Operations
ITF	=	International Transport Forum
LTA	=	Land Transport Authority
PKM	=	Passenger kilometers
PNT	=	Povcal Net Tool
$VTTS$	=	Value of Travel Time Savings
WTP	=	Willingness to pay

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II. Introduction

In recent years, there has been a significant increase in research interest in the field of urban air mobility (UAM). There are several projects under development and in operation within the context of air transportation services, capable of carrying passengers and cargo [1, 2]. The passenger-carrying UAM has the potential to bring various societal advantages, such as, reductions in congestion level, travel time, and emissions, as well as better accessibility to remote suburbs.

The extent of roadway congestion has surged in cities of all sizes since 1982, due to the growth in travel demand exceeding the growth of transportation capacity [3]. Following the historical trends of the economic growth, along with the expansion of the transportation system and the adoption of alternative modes of transport, the congestion cost in the United States (US) is projected to be up to $200 billion in 2025, resulting in a 20% increase from the 2017 value [4]. Roadway congestion across the urban areas in the United states in 2017 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. Congestion is a global issue, therefore an analysis of traffic design has been conducted across urban areas globally, resulting in the top eight most congested cities to be Bogota, Rio de Janeiro, Mexico City, Istanbul, São Paulo, Rome, Paris, and London [5]. Congestion has an adverse impact on many trip types including daily commutes.

The significant amount of waiting time in traffic reduces the velocity of travel and creates an environmental cost due to the massive amount of wasted fuel. In 2018, a total of around 24% of global CO_2 emissions come from fuel combustion in the transportation sector globally [6]. In order to address the problems associated with congestion and emission, the global transport network must grow and adopt new technologies at a faster pace than ever before. The introduction of Urban Air Mobility (UAM) could be a key solution to some of these challenges.

Over the past few years, technological advancements in battery capacity, sensors and microprocessors, GPS accuracy, autonomous software, noise reduction have strengthened the development of UAM concepts. The future economic growth relies on the recognition of the importance of UAM operations. According to the market study conducted by Booz Allen Hamilton (BAH), as of 2018, over 70 global manufactures, investors, operators, suppliers, and governments have financed more than $1 billion in urban air mobility technologies [7]. To understand the future of UAM fleet operations, it is necessary to evaluate the potential benefits of implementation of UAM concepts into urban transportation networks.

In the previous study by the research team, a top-down methodology was implemented to forecast the demand for UAM operations applicable to any global cities with fewer data requirements. The methodology was implemented for a set of 31 large cities that are expected to see UAM operation in the near term. A few assumptions were made in order to implement the methodology. The methodology predicted the demand forecast for 2035 and showed an indication of strong market demand for a range of UAM trip costs and vertiport infrastructure development [8]. The current study aims to build on the assumptions made in the previous work and generate a global UAM demand estimate for 542 of the top global cities between 2035 and 2050. In addition, long-term market demand scenarios are forecast exhibiting low and high penetration levels for UAM services are included in the research.

The paper is organized as follows: Background section provides the reader with an overview of existing research in the field of UAM demand estimates. This is followed by an explanation of the traditional four-step transportation model and its complexity in implementation for a large set of cities. A binary choice model considering the inherent benefits of travel time savings (VTTS) offers a solution and is explained in detail in the methodology section IV. This section also demonstrates the identification of 542 cities viable for UAM operation and a clustering approach to merge cities with similar characteristics. Together with the identification of viable cities for UAM operation, this section also defines the low and high demand scenarios and assumptions associated with them. The next section V explains the concept of operations and data requirements to execute the scenarios. The results of the implementation are presented in section VI; the discussion of results highlights the demand estimates of UAM services for the 542 global cities in terms of annual UAM passenger trips, annual UAM PKM, annual UAM utilization, and annual UAM vehicle trips. Section VII provides a concise summary of the developed approach to forecast global annual UAM demand. This section also provides remarks on the study and gives recommendations for future work. The last section VIII acknowledges the project sponsors and supporting individuals for their important contributions.

III. Background

The intent of this section is to provide an overview of the factors that may affect the demand of UAM services from operational and behaviour aspects. This paper focused on key demand driving parameters such as value of travel time savings (VTTS) compared to other alternate modes of transport, ticket price, trip purpose, trip distance, access time, egress time, household income, range and cruise speed. Currently, there are a large number of challenges (both technical and non-technical) and constraints associated with successful UAM operation. Technical barriers are related to air traffic management, battery technology, weather, economics, environmental impacts, and more. On the other hand, non-technological barriers are related to regulatory and certification issues, competition from existing modes of transportation, and infrastructure.

A market report by Booz Allen Hamilton (BAH) estimates the demand by calculating the total number of trips which can be captured by a novel class of vehicle services like UAM [7]. First, the total trip in each urban area is identified and categorized by travel type and mode type. Then, existing infrastructure is mapped, and a gravity model of origin-destination trips is created to identify the percentage of trips which provide travel time savings. At the end, willingness to pay, infrastructure capacity, time of day, and weather constraints are applied [7, 8]. Crown Consulting's (CCI) report takes a simpler and more transparent approach [9]. The demand is quantified by considering drivers involving the target market, consumer willingness to pay, and technology availability. The market size is calculated by multiplying the total number of expected trips in each city by the percent of trips which are eligible for UAM. That result is divided by the number of trips one UAM vehicle can make each year.

As the technologies are evolving, a large number of companies and start-ups have already embarked in the development of UAM vehicle for different cruise speeds, payload, ranges, and seating capacity. Table 1 specifies some of most common UAM vehicles manufactures with their vehicle specifications.

Table 1 UAM Vehicle Specifications

UAM Manufacturers	Speed (km/hr)	Range (km)	Seating Capacity
Volocopter [10]	110	35	2
Airbus Vahana [11]	220	50	1
City Airbus [12]	120	30	4
Joby Aviation [13]	320	240	4
Lilium [14]	300	300	5

The existing literature demonstrates that UAM services will have the capability to curb the problems associated with the congestion on the roadways traffic in urban areas. UAM will also have the potential to serve both inter and intra-city trips. A precise understanding of global UAM demands is very crucial for the city planning agencies, regulators and manufacturers. Till date, UAM demands have been explored only on a very small set of cities. This study aims to broaden the scope of analysis and investigates the global UAM demand for 542 cities for lower and higher demand scenarios.

IV. Methodology

A. Investigation of Demand Estimation Methodologies

Prediction of traffic facilitates public planning agencies to enhance decision making with respect to the development of roadway and transit infrastructure. In literature, the most widely used forecasting methodology is the four-step transportation model [15]. The first step in four-step traffic forecasting model initiates by dividing the region of study into discrete traffic analysis zones (TAZ). As the TAZs are identified, land use and socio-economic data for the region is gathered. Based on these demographics, the number of trips produced (i.e. origin) and attractors (i.e. destination) by each zone is identified. A detailed explanation of the four-steps transportation model is presented in previous work by the authors [8].

It is not possible is implement four-step transportation model for UAM service demand on global level since it requires a detailed demographics data, calibrated equations and framework capable of estimating trip counts and modal splits. Nevertheless, four-step transportation model can serve as a road map in developing novel approach.

B. UAM Demand Estimation Methodology

The novel developed UAM demand estimation methodology uses a generic top-down approach to estimate the UAM operations during 2035 to 2050 time period. Passenger demand, fleet size, and flight hours are the three main descriptors for quantifying UAM operations. All the three descriptors can be broken down as a function of UAM traffic in terms of passenger kilometer (PKM) travelled by UAM. Hence, the methodology must be capable of estimating the UAM PKM. 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 addressed by UAM is the percentage of the population that will choose to use UAM for a given trip instead of conventional ground-based transport. It is not feasible to perform an origin-destination (O/D) level analysis while considering millions of trips and PKM's globally, as it is computationally very expensive and data needed to support the analysis at this level is prohibitive.

The methodology follows the road map similar to traditional four-step transportation model. The first step involves the investigation of trip generation and trip distribution. These steps identifies the specific trips and their attributes to feed the modal split level which is responsible for assigning the trips to different modes. Trip data and relevant attributes at the city level are publicly available for the United States through the Department of Transportation, similar data is, however, much more limited globally. Nevertheless, some commercial vendors like INRIX and commercial software like TomTom can aggregate traffic data across global markets [16]. The subsequent step is modal split; modeling the consumer behaviour is an entire field of study on its own, and extensive studies have been conducted. The traditional four-step transportation model employs some type of utility discrete choice model which attempts to use trip attributes such as trip cost, trip time, convenience, comfort, wait time, and travelers' attributes such as income, sex, age, race, etc. to predict mode choice behavior [8]. Revealed preferences and stated preferences data are typically used to calibrate the consumer behaviour.

Revealed preferences data describes the historical traffic data while stated preference data implies to data gathered from surveys. Due to unavailability of any existing transportation option comparable to UAM, revealed preferences approach is non-feasible, conducting a survey to estimate the travelers preference is not plausible when analysing global more than 500 cities and also conducting survey for each state for stated preference data is outside the scope of this study. As a substitute, an approach considering the inherent benefits of UAM without the need of travelers' behaviour data is employed.

A potential advantage of UAM is the time savings accomplished by UAM trip instead of a conventional or alternate mode of transport. Accordingly, the decision made by a traveler with regards to the mode choice to use for the trip can be considered as a function of the value that travelers place on their time saved. Thus, by analysing the value of time, a travelers' willingness to pay (WTP) for a trip through a specific mode of transport can be calculated. A binary choice model developed by [17] suggests that if the traveler's WTP is greater than the price of UAM trip, then the traveler will adopt to UAM as their mode choice. WTP is estimated as the total value of time saved during a trip plus the cost of an alternate mode of transport. The calculation of WTP is shown by Equation 1.

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

The value of travel time savings (VTTS) is the value per unit time as a function of income of traveler and trip purpose. A paper from the US Department of Transportation suggests that VTTS varies in a range of 35% to 60% of earning per unit time for personal trips and between 80% to 120% for business trips [18].

As O/D-level analysis is prohibitive, the last step of the four-step transportation model, i.e., network assignment does not add any advantage to the demand estimation process. Hence, the conventional four-step transportation model is not feasible for this methodology. However, the model was used as a starting point to find alternative methods that demand a larger scale and scope.

1. Estimating Market Share for UAM

Using willingness to pay (WTP) for UAM services of a traveler to estimate their mode choice decision is a credible and favorable approach [17]. Equation 2 demonstrates the necessary conditions for an individual to select UAM services instead of an alternate mode of transport. After evaluating Equation 2 across the entire range of values for distance, income and trip purpose the viable space for UAM travel is identified.

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

2. Total Addressable Market

Total PKM is identified as a function of trip distance, trip purpose, household income, and trip mode. Traffic volume aggregated by each of these attributes is difficult to find for cities outside of the United States. When analyzing the 542 cities globally, it is infeasible to gather household income, trip purpose, trip distance, and travel mode data for all the cities. A search on public and commercial data sources has found that following types of data are available for many markets. Table 2 represents the available data sources.

Table 2 List of All Data Requirements & Inherent Proxy Data to Enable the Filling of Data Gaps

Data	Data Sources
Trip distance distribution for passenger vehicles at the city level	INRIX [16]
Total PKM across all ground modes at the country level	ITF [19]
Modal split of trips taken at the city level	LTA, Delolite [20, 21]
Share of trips by purpose at the country level	Literature [22]
Household income distribution at the country level	PwC [23]

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. Through these assumptions, the total PKM associated with a specific viable range of input variables is calculated as shown in Equation 3.

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

In Equation 3, 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 [8].

C. Identification of Cities Viable for UAM Operations

High and rising levels of congestion are driving the need for a new and faster modes of transportation. Roadway congestion has many causes, but the primary reason is the growth of population at a rapid pace. Cities with a higher number of inhabitants would have more likelihood to avail the UAM services. Nonetheless, sufficient population is needed for a city to be viable for UAM services. Population and economic indicators of a city plays an equally important role. The authors have selected population and GDP of a city as the filters to identify the global top 500 cities (approximate) that would be viable for UAM services in year 2035. City-level population data is publicly available from the source Demographia [24]. The publicly available Demographia data provides the ranking of 1,073 cities globally based on the population of the year 2019. A population growth percentage is applied on the Demographia data to forecast the 2019 city level population until the year 2050. This forecasting was facilitated using private data provided by the DLR (German Aerospace Center). A population of one million is the minimum requirement for the cities to be viable for UAM operations.

The second filter is an economic indicator as previously noted – the gross domestic product (GDP) of the city. The data is acquired from IHS Markit's Global Insight [25]. The proprietary data provides key economic indicators with historic data from 1970-2018, and forecasted data from 2019 to 2049. The $GDP_{percapita}$ is always represented on a country level; the country level $GDP_{percapita}$ is translated to city level GDP using Equation 4. The GDP filter for a viable city was set to five billion USD for the year 2019 and 100 billions USD for year 2050. When a filter of one million inhabitants on city population, five billion GDP for the year 2019 and hundred billion GDP for 2050 was employed, 535 global cities were found viable for UAM operations. To account for touristic cities that could benefit from UAM services, seven additional cities were added for the analysis.

$$(GDP)_{city} = (GDP)_{percapita} * (Population)_{city} \quad (4)$$

In summary, the authors identified 542 global cities viable for UAM operation during 2035 to 2050 time frame based on population and economies of the cities. The set of 542 cities represents 83 global countries viable to offer UAM services.

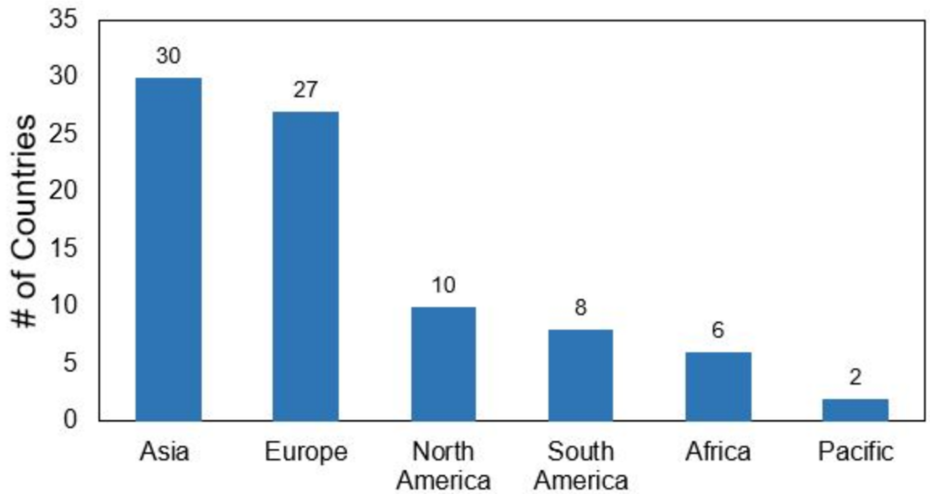


Fig. 1 Geographical Distributions of Global Countries Viable for UAM Services

Figure 1 visualizes that Asia region represents slightly more than 1/3rd of total countries among all the geographical regions. 27 countries in Europe may offer UAM services during the 2035 to 2050 time-frame. Around 10 countries in North America may facilitate the UAM services during 2035 to 2050 time period. Nearly 8 countries and South America and 6 in Africa may have the capability to smoothly facilate UAM services. In the Pacific region, Australia and New Zealand are the only two countries ready to offer UAM services during the 2035 to 2050 time-frame.

D. Clustering Approach

After the list of 542 cities viable for UAM operation is identified, the next step is to merge the cities with similar characteristics using clustering techniques. The purpose of doing this clustering is to execute dimensionality reduction. Conducting the forecasting process on all 542 cities would be both time- and data-intensive. These requirements are reduced by clustering cities with similar characteristics such that only a fraction of the cities need analyse, but they can numerically represent the remaining cities. A good clustering algorithm and its outcome should produce high-quality clusters in which intra-class similarity is high and inter-class similarity is low. Land area of city in 2019, population density of city in 2019 and GDP of city in 2019 and 2050 were identified as the descriptors to merge cities with similar characteristics.

More than a hundred clustering approaches have been proposed and studied to date. All these approaches can be be classified into five main subsets. Table 3 represents an overview of several kinds of clustering approaches.

Table 3 Classifications of Clustering Approaches

Types of Clustering Algorithms				
Partitional	**Hierarchical**	**Density Based**	**Mode Based**	**Grid Based**
K-means	Agens	DBSCAN	EM	WaveCluster
K-medoids	Diana	DBCLASD	COBWEB	CLIQUE
K-modes	BIRCH	DENCLUE	CLASSIT	OptiGrid
Fanny	CURE	Mean Shift		
CLARA	ROCK			

Partitional clustering is an iterative approach which discovers the affinity among inter cluster points w.r.t their distance from centroid of cluster. Hierarchical clustering initiates with a single cluster comprising all the data points. Afterwards, they are divided into discrete groups as their distance increases. The hierachy of the complete data set is usually shown in dendrogram. Density based clustering algorithm approach employs density of the data points in data space to form cluster. The regions with low density are used as partitions and regions with high density are separated as cluster. Model based clustering approach uses multiple pre-defined mathematical or statistical models to form clusters. Grid based clustering approach forms a uniform grid by collecting data from database using statistical tools. The performance of this approach is based on size of grid not on the size of actual data space [26].

In the current research, K-means clustering approach which is a type partitional clustering is implemented. K-means algorithm is one of the most famous and popular unsupervised machine learning algorithms to solve clustering problems. K-means algorithm aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. The cluster means are called cluster centres or cluster centroids. The algorithm starts with centroids chosen randomly, and as the algorithm evolves during the machine learning process, the clusters grow and absorb nearby observations. A new cluster centroid is computed for each cluster when the nearby observations are absorbed into the cluster. The algorithm stops when the cluster centroid movement is demonstrably small, implying that the clusters are converged and have negligible changes from one iteration to the next.

A statistical computer program JMP is used to execute the K-means clustering algorithm on the cities data. The tool JMP also provided cubic clustering criterion (CCC) value which helped the researchers to select the optimal number of clusters required for the data set. The CCC value is used to estimate the number of clusters using Ward's minimum variance method. Usually larger values of CCC represents better fit. The best fit is indicated with the designation optimal CCC in a column called best in the JMP. Twenty two is the optimal number of clusters identified by JMP to merge cities (542) with similar characteristics.

A representative city for each cluster is identified. For single-city clusters, the city itself is the representative city. For multi-city clusters, the representative city is the city with metrics that are closest to the statistical centroid of the cluster (assuming equal weighting of all attributes). In cases where a representative city is numerically indistinguishable, the subject matter experts' suggestions from DLR and Georgia Tech were incorporated to select the representative city in each cluster.

E. UAM Forecasting Scenario Generation

To capture the inherent uncertainties associated with UAM demand estimates, different assumption were made to evaluate the lower and higher bounds. The high demand scenario includes matured market conditions compared to prematured conditions for low demand.

1. UAM Forecasting Scenario Definition

High and low demand scenarios are defined in the current work to capture the upper and lower bounds of UAM demand estimates during the 2035 to 2050 time-frame. In the low demand scenario, the UAM services attract higher-density business travel routes used by a customer base that is not price sensitive. The services are used only within metropolitan areas.

The high demand scenario refers to a condition where the usage of UAM service expands beyond the metropolitan areas. The services additionally show a free flight scenario, i.e. UAM services moves within the city and between city pairs. Airport shuttles and intra-city operations are applicable.

2. UAM Forecasting Scenario Assumptions

UAM demand forecast is highly sensitive to the assumptions made during formulation. The average speed of UAM vehicle is assumed to be 120 km/hr for low demand scenario and 240 km/hr for high demand scenario. The researchers assumed that there will be one vertiport every 300 sq.km in low demand scenario. For instance, for a city like London which has around 1,800 sq.km of land area there will be 6 vertiports in the low demand scenario and 15 vertiports in the high demand scenario to offer UAM services. VTTS is assumed at 35% and 80% for personal and business trips respectively for low demand scenario and 60% and 120% respectively for high demand scenario. Table 4 presents the list of assumptions made during the research to execute the scenarios.

Table 4 UAM Forecasting Scenario Assumptions

Assumptions	Low Demand	High Demand
Average Speed of UAM Vehicle (km/hr)	120	240
Range of UAM Vehicle (km)	60	120
Vertiport Density (sq.km)	300	120
VTTS (Personal, Business)	35%, 80%	60%, 120%

V. Implementation

A. Enabling Data for UAM Demand Forecast

While addressing a global scope of cities, major issues arise regarding the availability of data, budget constraints or processing, and resource constraints. Partial traffic data has been acquired from commercial vendor INRIX [16], and regression models were built using the available data to estimate data gaps. Publicly available data is sparse for cities outside of the United States. A technique is developed to fill those data gaps and is explained in the following sections.

The methodology described aims to generate demand estimates for the 542 cities between 2035 and 2050 for both the high and low demand scenario assumptions. The list of global 542 cities was generated using population and economic indicators of the cities.

Estimation of global demand for urban air mobility networks is highly dependent on the assumptions made to generate them. Some of the assumptions that will be made to generate the data required will be discussed in the following subsections.

1. Concept of Operations

In order to implement the developed methodology, it is a prerequisite to define the concept of operations (CONOPS). Figure 2 demonstrates the UAM Concept of operations.

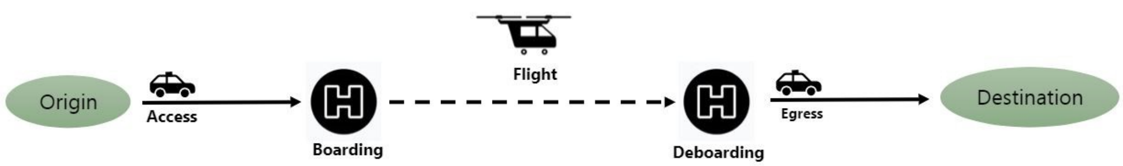


Fig. 2 Concept of Operations (CONOPS)

A ride-share option is used to arrive at a dedicated vertiport. A vertiport is defined as an urban location from which a vertical take-off and landing vehicles can operate. A helipad is considered a vertiport, but in the future, it is expected that UAM infrastructure development will include vertiports that look and operate differently than the heliports that exist today. The distance travelled from the origin to the vertiport is defined as access trip distance. Once at the vertiport, the traveler completes the security check, walks to the UAM vehicle, and boards the vehicle to initiate the services. The flight occurs at a constant cruise speed of 120 km/hr for the low demand scenario and 240 km/hr for the high demand scenario. As the flight reaches the destination vertiport, the traveler de-boards the UAM vehicle, exits the vertiport, and uses a second ride-share option to reach their final destination. The distance between the de-boarding vertiport and the travelers' final destination is defined as egress trip distance.

Next, the access and egress trip distances are calculated as functions of vertiport network density. A grid-like distribution for the vertiports is assumed. For high demand scenario, there is one vertiport in every 120 sq. km of city's land area. The average access and egress distance (d_v) is assumed to be 2/3rd of the maximum distance to the vertiport within one of the grid elements of the network. The total UAM trip distance (d_t) calculated by Equation 5 as the flight distance (d_{flight}), the access and egress trip distances, assumed to be equal.

$$d_t = 2 * d_v + d_{flight} \tag{5}$$

The maximum access and egress trip distance is estimated to be ~ 5 km in the high demand assuming that one vertiport is located every 120 sq. km of the city. In low demand scenario, the maximum access and egress trip distance will be approximately ~ 8 km assuming one vertiport would be available in every 300 sq. km of the city's land area.

2. UAM Ticket Price

Trip price for UAM is the summation of the prices associated with access trip, actual flight, and egress trip distances. Mathematically, UAM ticket prices is written as shown in Equation 6

$$Price_{UAM} = Price_{access} + Price_{flight} + Price_{egress} \tag{6}$$

The access and egress distances are assumed to be covered by a ride-share option. The price of a ride-share option is estimated to be 2 $/mile in the United States based on the price estimates of popular ride-share services and is adjusted across all global markets based on the cost-of-living index (CoL). cost-of-living index information is sourced from Numbeo and WorldData.info [27, 28]. WorldData.info builds its database from OECD, IMF, Eurostat, Numbeo, and its own research. The price related to access and egress distance covered by ride-share option is assumed constant for all the future years within time-frame of 2035 to 2050. Due to lack of historical data, flight price must be estimated. Some of the available market reports develop price models and report a wide range of possible ticket prices for UAM services in both near and long terms. A report by Booz Allen Hamilton estimates the price of UAM ticket to be $11.00 per passenger per mile (~ 6.83 per passenger per kilometer) and $6.25 per passenger per mile (~ $3.88 per passenger per kilometer) for a 5-seater UAM vehicle [7]. A study by Uber estimates the UAM ticket price to be ~ $1.30 per passenger per kilometer in the near term and ticket price is expected to drop $ 0.43 per passenger per kilometer [29]. Market report by Crown Consulting Inc, proclaims the average UAM ticket price to be $0.93 per passenger kilometer [9].

To account for the sensitivities associated with the price of flight for UAM services, price of flight in a range of $0.50 per passenger kilometer to $7.50 per passenger kilometer is evaluated. This wide range of prices is chosen to capture as many potential outcomes as possible. Annual UAM passenger trips, annual UAM passenger kilometer (PKM), annual UAM utilization, and annual UAM vehicle trips are computed for each price metric for both high and low demand scenarios for the time frame 2035 to 2050.

3. UAM Trip Time

UAM is a multi-modal travel option, where a traveler must take some secondary mode of transport to arrive and depart from the origin and destination vertiports. The total trip time for UAM is the summation of time to access, time to board, time for actual flight, time to de-board, and time to egress, shown mathematically in Equation 7.

$$T_{UAM} = T_{access} + T_{board} + T_{flight} + T_{deboard} + T_{egress} \tag{7}$$

The CONOPS considered in the study assumes access and egress distance is covered by the ride-share option, and access and egress times are calculated using the personal vehicle speed curve of the representative city. Boarding time is assumed to be 5 minutes, and de-boarding time is assumed to be 2 minutes. Boarding time includes the time to enter the vertiport, complete the security check, walking to and boarding the UAM vehicle. De-boarding time includes time to exit the UAM vehicle and the vertiport. The flight time is computed using constant cruise speed following the point-to-point ground distance. The average speed of UAM is assumed to be 120 km/hr in low demand scenario and 240 km/hr in high demand scenario.

4. Cost of Alternate Modes

According to AAA, [30] the current cost of operating a personal vehicle in the United States is assumed to be around $0.37/km. To analyse the intra-city ticket prices (by bus or metro) for a list of 542 cities is very cumbersome. The list of selected 542 cities viable for UAM operations represents 83 countries globally. The researchers collected the one-way public transit (bus/tram/metro) ticket prices for the capital cities of all 83 countries and averages the collected ticket price to obtain a global average of the intra-city ticket price. To account for inter-city trips, the authors collected the bus and train ticket prices to travel a distance of 300 km from the cities. Around 25% of countries from each region are selected from the list of 83 global countries, and inter-city trip price is collected for both bus and train services. An averaging is performed to aggregate the inter-city ticket fairs in each region, and global averaging is conducted to account for the global average intercity ticket price. The global-averaged inter-city and intra-city ticket prices are presented in Table 5. The cost of all alternate modes is assumed constant as per current market conditions for the analysis until the future year (2050). The ticket prices are adjusted according to the cost-of-living index for each country during implementation.

Table 5 Global Average Ticket Price for Inter-City Bus Intra-City Bus

Global Average Ticket Price	Inter-City Bus	Intra-City Bus
Euro (€)	22.70	1.20
USD ($)	27.20	1.40

5. Parking Costs of Alternate Modes

Cost of travel is the product of distance travelled and cost per km. Total trip cost by private transport is the sum of travel cost and parking cost. The average parking cost in the capital cities of 83 countries are gathered from parkopedia [31]. An average for these cities is completed for parking costs to select a global average parking cost. Four-hour parking cost is incorporated as an average to support accounting of total trip cost by alternate modes of transportation. The average four-hour parking cost is computed and recorded as $7.48. Parking costs are further adjusted according to the cost-of-living (CoL) index for all the countries during the actual UAM forecasting computation processes.

6. Value of Travel Time Savings

According to the US Department of Transportation (DOT) on the valuation of travel, VTTS has been defined for personal trips and business trips. The US DOT suggests that VTTS for a personal trip can vary in a range of 35% to 60% of income per unit time while for business trips VTTS can vary in a range of 80% to 120% of income per unit time [18]. It is assumed that hourly income rate VTTS values are 35% for personal trips and 80% for business trips in the low demand scenario. In the high demand scenario, hourly income rate VTTS is assumed as 60% for personal trips and 120% for business trips.

7. Travel Time of Alternate Modes

UAM services will be competing with currently available modes of roadways transportation. Computing door-to-door travel time for personal and public transit depends heavily on the route and time of day. Performing origin-destination level evaluation is computationally expensive. Speed of trip is a function of trip distance, shorter trip distances yield slower averages while longer trip distances show a faster average speed. To model this relationship, several trip distances between 5 km and 120 km are sampled for all the representative cities. A logarithmic model as shown in Equation 8 is used to fit the sampled data.

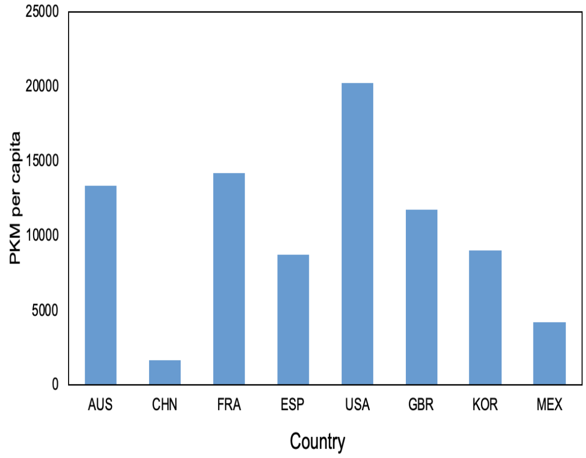
$$Speed_m(d) = a_m * ln(d) - b_m \tag{8}$$

In the Equation 8, $speed_m$ is the speed by an alternate mode of transport (m), d is the distance traveled by an alternate mode of transport (m), a_m and b_m are the logarithmic coefficients.

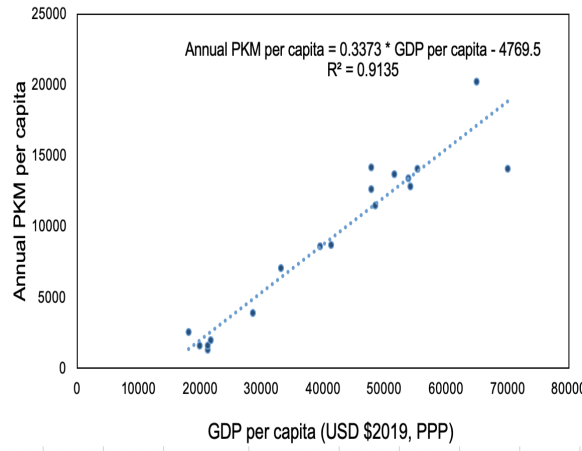
8. Total Ground PKM

Total ground PKM data is sourced from ITF Transport Outlook for the year 2019 [19, 32]. This source provides country-level PKM data for Australia, China, Spain, France, Great Britain, South Korea, Mexico, and the United States, shown in Figure 3a.

The total ground PKM per capita is calculated between 2035 and 2050. An assumption is made that the growth of population is directly proportional to the growth of total ground PKM [33]. This assumption helps the researchers in forecasting the total ground PKM between 2035 and 2050. During the forecast, population growth rate percentage provided by the DLR was used to scale city population. A linear regression is built between GDP per capita and PKM per capita to fill the data gaps for the countries with which PKM information is not available via ITF Transport Outlook. The regression model is shown in Figure 3b.



(a) Total PKM per Capita Travelled by Country [19]



(b) Annual PKM per Capita vs GDP per Capita

Fig. 3 Total Ground PKM and Linear Regression between Annual PKM per capita vs GDP per capita

9. Modal Split

Modal split data is collected from Singapore's Land Transport Authority (LTA) Academy [20], shown in Figure 4, and Deloitte's City Mobility Index report [21]. The resources collect mode shares as reported by local governments across global cities. The modal splits consist of private transport, rail, bus, taxi, cycle walk, and others. Since cycling and walking trips are usually chosen for small distances, these modes are not used and new mode shares are calculated.

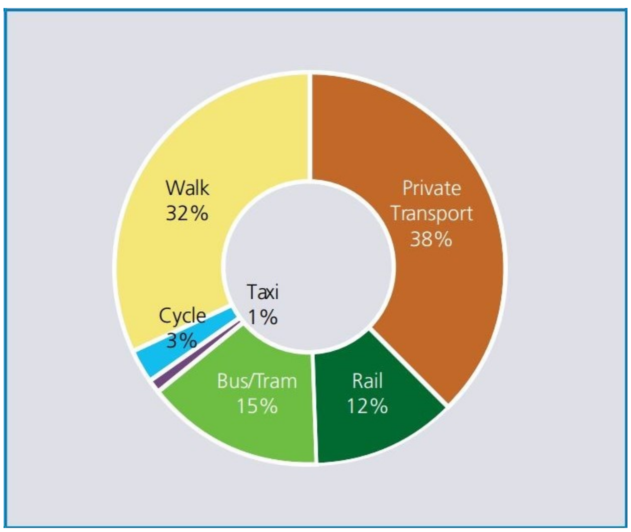


Fig. 4 Total Ground Transport Mode Shares in London [20]

10. Trip Purpose Split

The availability of trip purpose split data is very limited. A report by the EU Joint research committee has published the results from EU country's survey reports, stating that only 5% of the trips are for business purposes whereas 95% of the trips are for personal travel. The personal travel includes travel for education, shopping, leisure activities etc. A few other literature quotes slightly different percentages for business and personal travel [22]. The current research assumes that 6% of trips for business purposes and 94% of trips are for personal purposes. These percentages remain constant for both high and low market demand scenarios across all the forecasted years.

11. Trip Distance Distribution

Trip distance distribution data for the 22 representative cities is sourced from commercial supplier INRIX. The commercial vendor INRIX's trip distribution data provides more accurate insight into the trips people take, including beginning, ending, and waypoint locations. INRIX uses geospatial data processing tools to enable the understanding of population movements with attributes such as origin and destination zones, diversion routes during peak hours and accidents, corridor usage statistics, and more. The data also provides the trip counts for a range of trip distances for all the representative cities. Figure 5 represents a sample of trip distance plotted against percentage of trips in Chicago. A log-normal distribution is fit with the help of statistical tool JMP to each of the traffic pattern data types for the representative cities. The log-normal regression for each representative city is applied to all the cities within a cluster.

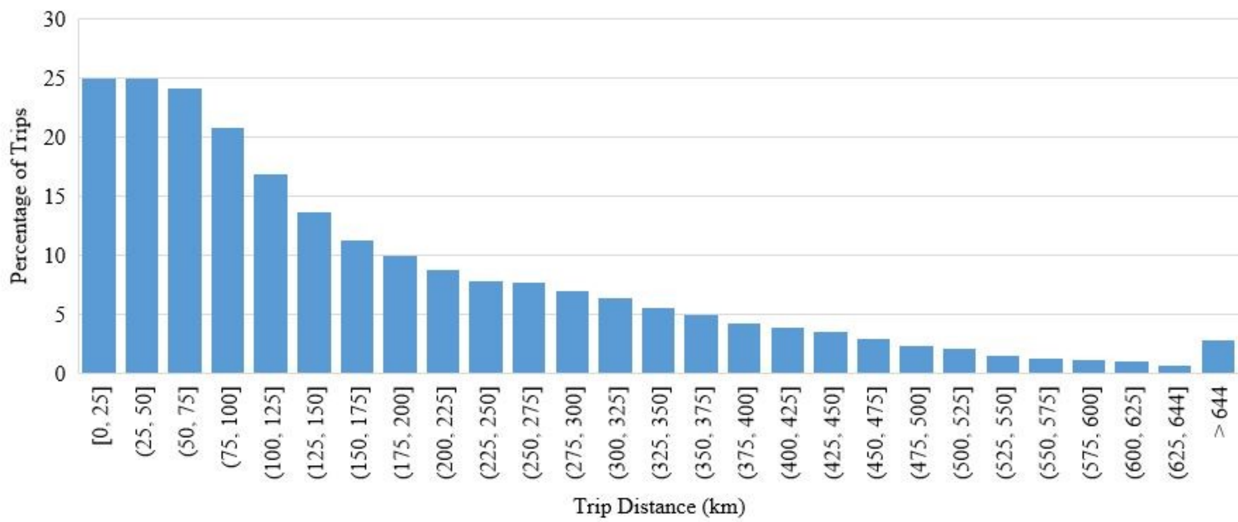
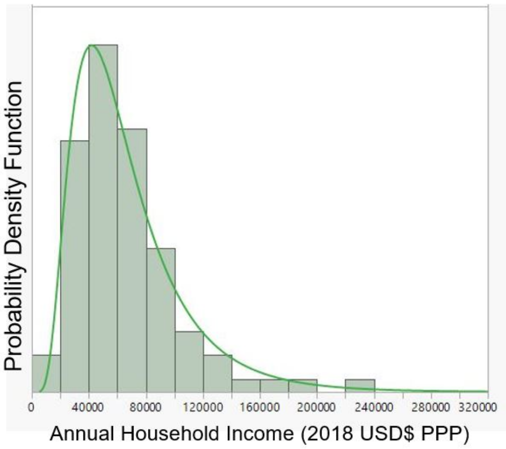


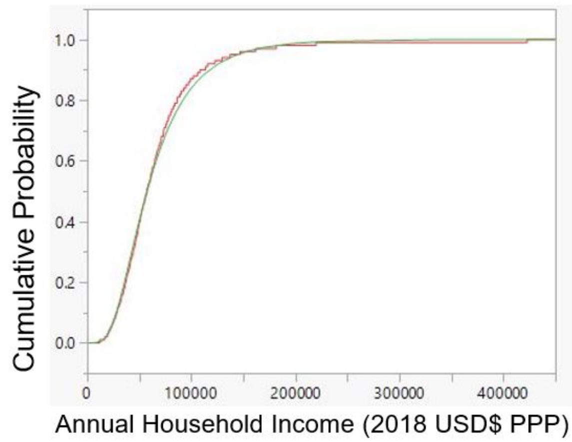
Fig. 5 Sample Trip Distance Distribution Data

12. Household Income Distribution

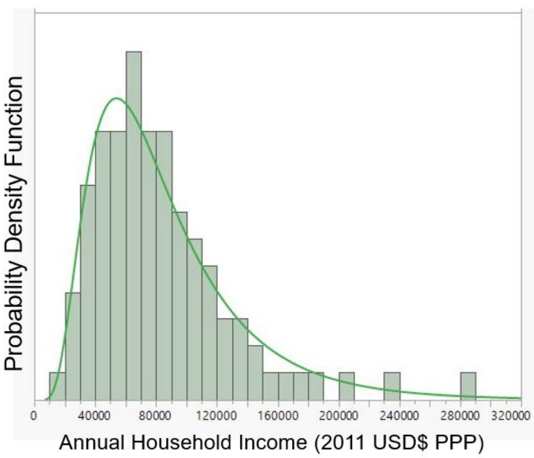
The city-level household income distribution is not available publicly for any global city of interest. To overcome this shortage, country-level income distribution is assumed to be equal to city level household income distribution. Country-level income distribution is sourced from the World Bank's Povcal Net Tool (PNT) [34]. The PNT provides information related to income level within a country based on quantiles of population percentage and cumulative wealth percentage. Future income information can be forecasted using the average annual inflation rate of the country. The average annual inflation rate data is sourced from PwC's global economic projections [23]. The source provides an inflation rate forecast between 2022 and 2026 for 25 countries. Unfortunately, long term inflation rate forecast is not available. For the other countries, a twenty-year averaged historical inflation rate from the IMF World Economic Outlook [35] is used to create the income distribution matrix. Functions are fitted for each data set using JMP. As an example, the probability density function and cumulative distribution function of household income of France for 2035 are shown in Figure 6a and Figure 6b and for 2050 are shown in Figure 6c and Figure 6d.



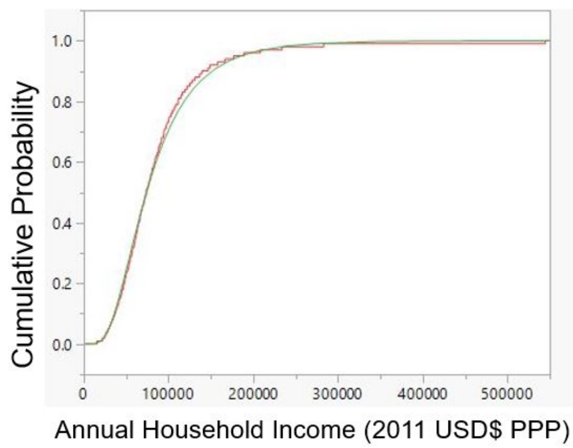
(a) 2035 Probability Distribution Function



(b) 2035 Cumulative Distribution Function



(c) 2050 Probability Distribution Function



(d) 2050 Cumulative Distribution Function

Fig. 6 Statistical Income Distributions for Household Income Distribution of France for 2035 and 2050 [34]

13. Range & Cruise Speed

The range and cruise speed of UAM vehicles are also considered as an important factor for the growth of demand for UAM services during the forecast time-frame. Several UAM vehicle manufacturers claim different range and cruise speeds for their UAM vehicles. Table 1 represents the vehicle specifications of some of the popular UAM manufacturers. A German-based UAM vehicle manufacturer Volocopter, claims that their vehicle has a top speed of around 110 km/hr with a range of 35km [10]. A study by Uber mentions that minimum desirable speed of UAM will be 240 km/hr where the optimal speed is a trade-off between propulsive efficiency and vehicle productivity to amortize the costs [29]. Due to uncertainty in the future UAM vehicle speed and range, this study assumes the average speed and range of UAM to be 120 km/hr and 60 km respectively in the low demand scenario and 240 km/hr and 120 km respectively in the high demand scenario.

VI. Results

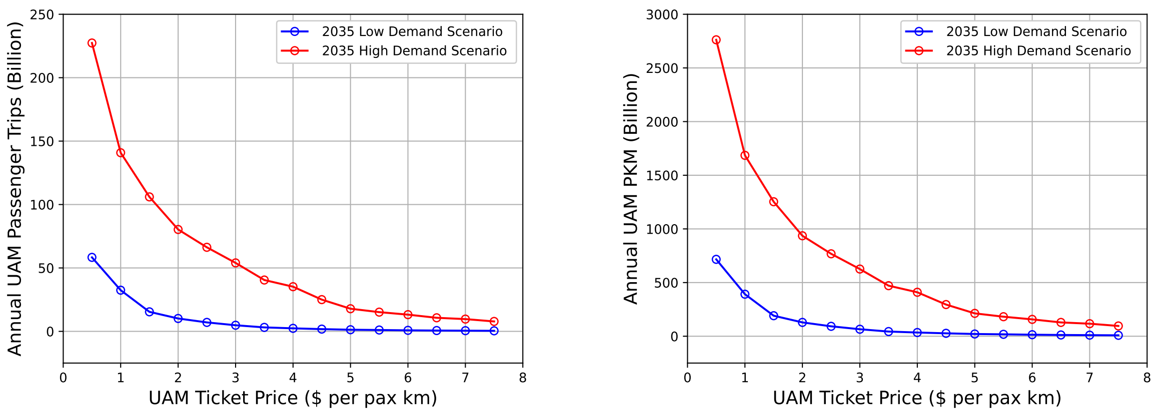
This section has been divided into three subsections. The first subsection presents a comparison between the high and low demand results to highlight the sensitivities related to the assumptions made during the research. In this first subsection, only the results from 2035 are discussed because the 2050 results show the same trends, so providing those plots would be repetitive. These trends are shown in more detail in the remaining two subsections, which exhibit the results individually for the low and high demand scenarios for all years between 2035 to 2050 with five-year intervals.

A. Comparison of Low and High Demand Scenario Outcomes for UAM

1. 2035 Annual UAM Passenger Trips and 2035 Annual UAM PKM

The annual UAM passenger demand estimates for all 542 cities considering the low and high demand scenarios for the year 2035 is represented in Figure 7a. The annual UAM passenger demand estimate is 58 billion in low demand scenario for the minimum ticket price of $0.50 per passenger kilometer. This number is expected to grow by a factor of 3.9 to 227 billion in the high demand scenario. As the UAM ticket price increases, a precipitous decrease in predicted annual UAM passenger trips is observed.

The annual UAM PKM estimates for 2035, shown in Figure 7b, the plot shows a very similar trend to that of UAM passenger trips in the previous subsection. Annual UAM PKM for all the global 542 cities grows by a factor of 3.9 from low to high demand scenario at the minimum ticket price for the year 2035.



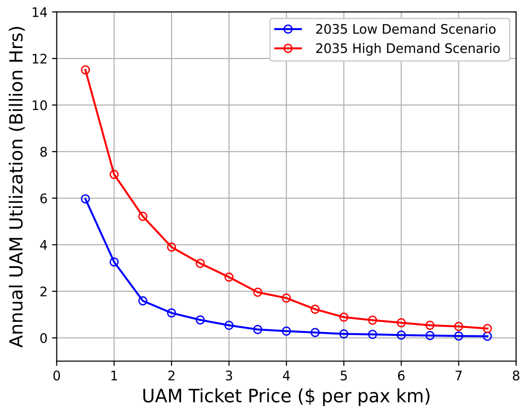
(a) Annual UAM Passenger Trip Results for 2035 **(b) Annual UAM PKM Results for 2035**

Fig. 7 Results for Annual UAM Passenger Trips vs UAM Ticket Price and Annual UAM PKM vs UAM Ticket Price

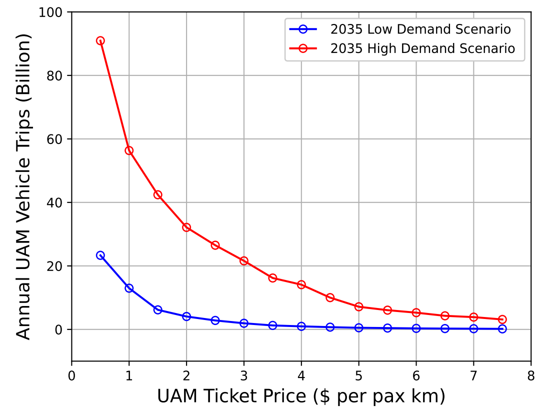
2. 2035 Annual UAM Utilization and 2035 Annual UAM Vehicle Trips

The annual UAM utilization is a function of annual UAM PKM and the average speed of the representative UAM vehicle. As discussed previously, the low demand scenario average speed of UAM vehicle is assumed to be around 120 km/hr and in the high demand scenario, the average speed of UAM vehicle is 240 km/hr. The average speed of UAM is inversely proportional to the utilization of UAM vehicles. The results lead to the conclusion that the average speed of UAM does not affect the demand for services significantly. Figure 8a illustrates the results for annual UAM utilization for high and low demand scenario for the year 2035.

The annual UAM vehicle trip is a function of annual UAM passenger trips and the average number of passengers per trip. According to the vehicle specification by several global UAM manufacturers, the maximum seating capacity of UAM vehicle is around 5 people [14]. During the study an average of 2.5 passenger is assumed as a seating capacity of UAM vehicles and is kept the same in both low and high demand scenarios. Figure 8b illustrates the annual UAM vehicle trips for high and low demand scenarios for the year 2035.



(a) Annual UAM Utilization Results for 2035



(b) Annual UAM Vehicle Trips Results for 2035

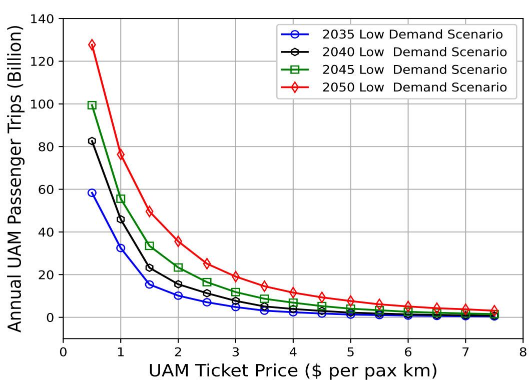
Fig. 8 Results for Annual UAM Utilization vs UAM Ticket Price and Annual UAM Vehicle Trips vs UAM Ticket Price

B. UAM Low Demand Scenario Outcomes

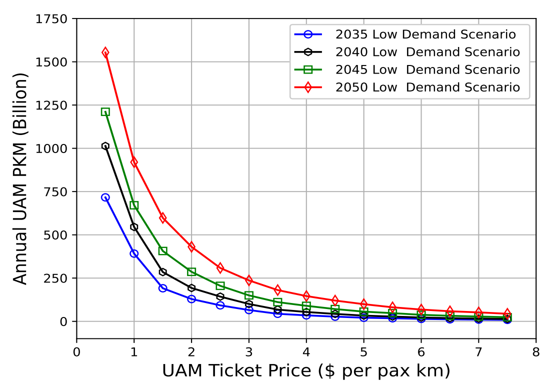
1. Annual UAM Passenger Trips and Annual UAM PKM for Low Demand Scenario

Annual UAM passenger trips for 2035 to 2050 in the low demand scenario are reproduced in Figure 9a. From the figure, it can be observed that the annual passenger estimates increase every year over the five-year intervals. Annual passenger trips for the low demand scenario in 2035 is around 58 billion. On an interval of five years, the annual passenger trips demand increases to 82 billion and continue to increase for the remaining future years. Decreasing the price of UAM services leads to exponential UAM demand growth.

The results of implementation for annual UAM PKM for low demand are shown in Figure 9b. A progression in the values of annual UAM PKM can be seen from the year 2035 to 2050 at each UAM ticket price. Lower values of ticket prices result in higher values of UAM PKM while higher ticket price decreases the annual UAM PKM tremendously for all the years.



(a) Annual UAM Passenger Trips Results for Low Demand



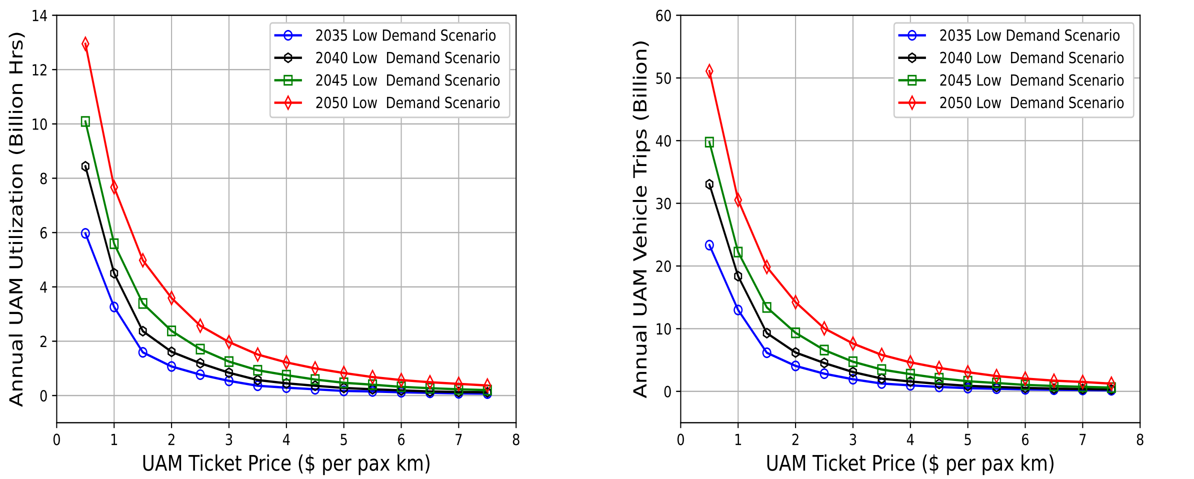
(b) Annual UAM PKM Results for Low Demand

Fig. 9 Results for Annual UAM Passenger Trips vs UAM Ticket Price and Annual UAM PKM vs UAM Ticket Price for Low Demand Scenario

2. Annual UAM Utilization and Annual UAM Vehicle Trips for Low Demand Scenario

The utilization of UAM services is related to UAM PKM and the average speed of UAM. The average speed of UAM vehicle varies in low and high demand scenarios. The high demand scenario corresponds to the higher value of average speed for UAM vehicle and the low demand scenario accounts for lower average speed. The annual UAM utilization for low demand scenario for 2035 to 2050 time frame is shown in Figure 10a.

As the number of passenger trips increases, the vehicle trips of UAM will grow accordingly. For simplicity in implementation, the average passengers per trip are assumed to be 2.5 due to several global UAM manufacturers claiming to have a maximum seating capacity of 5 passengers in the UAM vehicle and choosing half of this value as average. The results for average UAM vehicle trips in low demand scenario during the year 2035 to 2050 with five-year intervals are shown in Figure 10b.



(a) Annual UAM Utilization Results for Low Demand

(b) Annual UAM Vehicle Trips Results for Low Demand

Fig. 10 Results for Annual UAM Utilization vs UAM Ticket Price and Annual UAM Vehicle Trips vs UAM Ticket Price for Low Demand Scenario

Table 6 summarizes the outcomes of implementation for low demand scenario during the 2035 to 2050 time period.

Table 6 Low Demand Scenario Outcomes

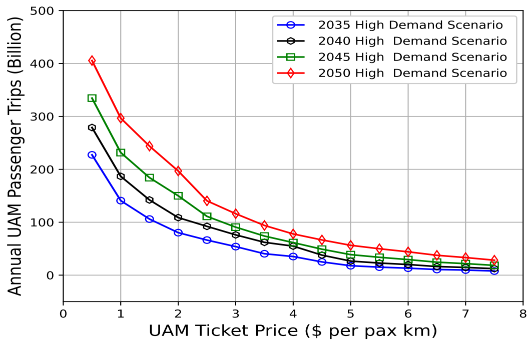
Annual UAM Outcomes	2035	2040	2045	2050
Annual UAM Passenger Trips (Billion)	58.34	82.61	99.41	127.8
Annual UAM PKM (Billion)	716.4	1013	1211	1554
Annual UAM Utilization (Billion Hours)	6.043	8.447	10.09	12.95
Annual UAM Vehicle Trips (Billion)	23.33	33.04	39.76	51.09

C. UAM High Demand Scenario Outcomes

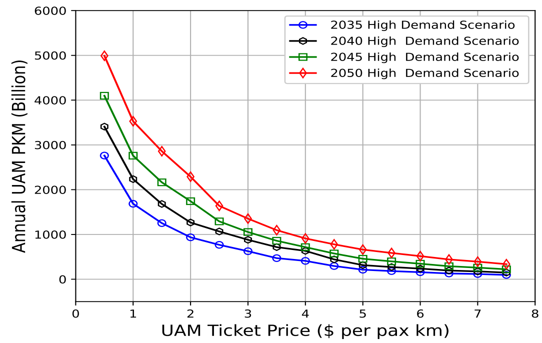
1. Annual UAM Passenger Trips and Annual UAM PKM for High Demand Scenario

The results for annual UAM passenger trips for the high demand scenario is generated in Figure 11a. The estimated demand for services for each five-year interval in the high demand scenario results grows by a factor of 1.2, reflecting a large market for the UAM services in future years if the prerequisites are obtained. These prerequisites include UAM vehicle production, vehicle safety, and certification standard development, and regulatory processes, among other challenges in getting the services to market.

The annual UAM PKM trend for all forecast years is shown in Figure 11b. A significant demand exists over the wide range of ticket prices considered in the study.



(a) **Annual UAM Passenger Trips Results for High Demand**



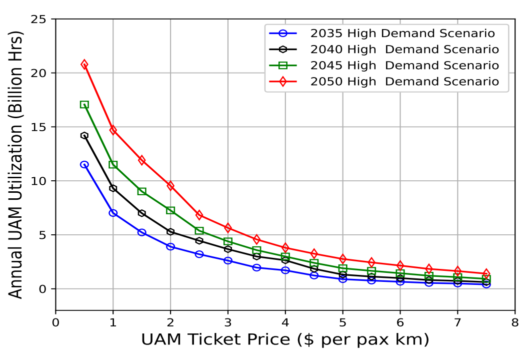
(b) **Annual UAM PKM Results for High Demand**

Fig. 11 Results for Annual UAM Passenger Trips vs UAM Ticket Price and Annual UAM PKM vs UAM Ticket Price for High Demand Scenario

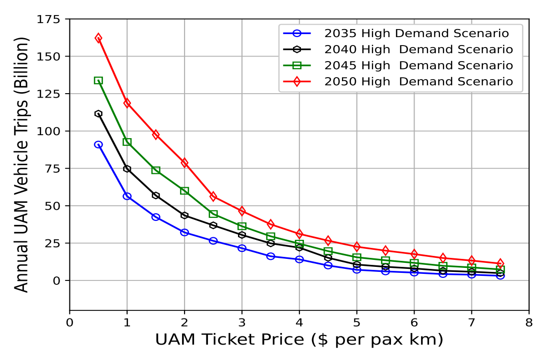
2. Annual UAM Utilization and Annual UAM Vehicle Trips for High Demand Scenario

The results for the implementation of annual UAM utilization for high demand scenarios are presented in Figure 12a. Utilization is related to annual UAM passenger trips and the average speed of UAM. Even though the average speed of the assumed UAM vehicle is significantly higher in the high demand scenario compared to the low demand scenario, the utilization of the UAM vehicles does not grow significantly. This result implies that the average speed does not significantly affect the demand for UAM services.

The number of vehicle trips for UAM grows as well in high demand scenario. At the ticket price of $0.50 per passenger kilometer, the number of annual UAM vehicle trips is expected to be around 90 billion in the year 2035 and is expected to grow by 162 billion by the year 2050 shown in Figure 12b . This growth in vehicle trips suggests that demand for services exists and will grow as population and global wealth grow in the future forecast years.



(a) **Annual UAM Utilization Results for High Demand**



(b) **Annual UAM Vehicle Trips Results for High Demand**

Fig. 12 Results for Annual UAM Utilization vs UAM Ticket Price and Annual UAM Vehicle Trips vs UAM Ticket Price for High Demand Scenario

Table 7 summarizes the outcomes of implementation for high demand scenario during the 2035 to 2050 time period.

Table 7 High Demand Scenario Outcomes

Annual UAM Outcomes	2035	2040	2045	2050
Annual UAM Passenger Trips (Billion)	227.3	279.1	334.5	405.5
Annual UAM PKM (Billion)	2762	3408	4098	4990
Annual UAM Utilization (Billion Hours)	11.51	14.21	17.07	20.79
Annual UAM Vehicle Trips (Billion)	90.94	111.6	133.8	162.2

VII. Conclusion

A. Summary

This study employed a top-down methodology to forecast the demand for UAM services during 2035 to 2050 time-frame for low and high demand scenarios for 542 global cities spread across 83 countries. A binary choice model considering the inherent benefits of the value of travel time savings (VTTS) is used instead of the traditional four-step traffic forecasting model due to its particular relevance for this new mode of transportation. A set of trips viable for UAM travel are identified by comparing the willingness to pay (WTP) for travelers on UAM trips with the price of UAM trips. The model assumes that all trips with higher WTP than UAM trip price will convert mode choice to UAM. All the trips identified as UAM trips are evaluated to estimate the total volume of ground traffic in passenger kilometer (PKM). To execute the scenarios, several metrics related to traveler income, trip distance, trip purpose and alternate modes are evaluated. Further, by aggregating the volume of traffic across all viable trips, the annual trips for UAM are estimated. Annual passenger trips, annual UAM PKM, annual UAM utilization, and annual vehicle trips are derived and presented for low and high demand scenario for the time-frame of 2035 to 2050.

B. Further Remarks

The estimated demand for annual UAM services is highly sensitive to the assumptions made in the study. A progression in demand for the UAM services is seen for both high and low demand scenario on year-over-year growth bases. UAM ticket price and demand for services show an inverse relationship such that decreasing the ticket price of UAM travel leads to an exponential increase in UAM services. Cruise speed and range of the assumed UAM vehicle is altered between low and high demand scenarios. The results show that cruise speed does not significantly impact the demand for UAM services. From the trends shown in the UAM results section, the demand for UAM services grows significantly when the ticket price drops below $3.00 per passenger kilometer. This value is a global average, and it can be adjusted to create a city or region-specific estimates using the cost-of-living index. If manufacturers and operators can work together to keep the ticket price below this level, then Urban Air Mobility is more likely to succeed from a global perspective of demand.

C. Future Work

The willingness to pay (WTP) function currently only considers quantitative choice attributes. A different approach that incorporates qualitative attributes, for instance, the comfort of travelers, the convenience of travelers, or the perception of waiting times. A rudimentary origin-destination level analysis based on city data such as land area and population distribution (achievable through isochrone maps, for example) would be valuable to strategically place vertiports and estimate trip times for UAM and alternate modes. In addition, parameters such as transportation cost and household income used in this study are based on current estimates and do not evolve for future years. This could potentially be supplemented with additional data or forecasts to improve the rigor of the economic analysis.

VIII. Acknowledgement

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