Analysis of Potential Demand of On-Demand Urban Air Mobility Via Agent-Based Simulation

by

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B.S. in Civil Engineering, Carnegie Mellon University (2020)

Submitted to the Department of Civil and Environmental Engineering
in partial fulfillment of the requirements for the degree of

Master of Science in Civil and Environmental Engineering

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2022

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Abstract

This thesis analyzes the potential demand of Urban Air Mobility (UAM) by performing agent-based simulation. The comprehensive UAM model proposed by this thesis combines demand, supply, and their interactions at fine spatial and temporal levels. It has been implemented in the state-of-the-art mobility simulation platform, SimMobility, and includes the following considerations: (i) demand-centric vertiport placements and realistic vertiport capacity generation; (ii) explicit service operations that include rebalancing, charging and transition activities at vertiports; (iii) a behaviorally sound decision-making process capturing the switching behaviors. Simulations of at-launch, near-term and long-term scenarios, varying in capacity, accessibility, and pricing constraints, are performed for two real U.S. cities, along with the uncertainties. The results show that UAM presents a niche market, with only a penetration rate of 1.45% to 1.81% even in the long-term scenario for the two cities studied. Furthermore, the potential UAM users are primarily high-income and car-oriented, indicating equity issues. Work and drive-alone trips have the highest penetration rate, and short-range trips constitute the majority of the UAM potential demand. Lastly, capacity, accessibility, and pricing show significant impacts on demand, which are city-specific effects. This thesis contributes to the literature by analyzing the impacts of UAM on mobility pattern, specifically focusing on the potential market size and demand characteristics under various supply configurations, allowing policymakers and the industry to make informed decisions regarding UAM market diffusion.

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Acknowledgments

First, I would like to express my sincere gratitude to Prof. Moshe Ben-Akiva for his guidance and patience. His invaluable suggestions and high standards pushed me to learn to be a researcher who always thinks critically, which is as important as the knowledge I have learned from him.

I would also like to extend my deepest gratitude to Dr. Ali Shamshiripour. This thesis would not have been completed without his patient support. I really appreciate the times when he helped me work through problems and provided invaluable insights. I would also like to thank Dr. Ravi Seshadri, Dr. Andre Romano Alho, and Dr. Md Sami Hasnine for their help throughout this research project.

I must also thank Lisa Yoo for her work in developing the supply-side software. Besides the research work, I would like to thank Lisa for the emotional support that she offered during the pandemic. I'd like to also recognize the assistance from Daniel Feldman.

I would like to thank my labmates Emma, Yifei, Siyu, Youssef, and Peiyu. It has been a pleasure working with and talking to all of them. I want to thank our lab administrator Katie Rosa as well for her support.

I am extremely grateful to my family in China, and all my friends. The time I spent at MIT has been accompanied by the pandemic and quarantine, which created stresses that I could not have resolved by myself. I sincerely wish we would reunite in the near future. I would also like to thank my boyfriend Matthew Kong, for his love and support.

Last but not least, I am also grateful to Ferrovial for sponsoring this research project.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

The advancements in automation, electrification, and communication technologies have brought new opportunities to the transportation sector in recent years, transforming the city landscape and individuals' behaviors. As one of the most recent innovations, Mobility on Demand (MoD), which provides on-demand services, has caused significant changes and is still evolving with the new technologies: e.g., Autonomous MoD (AMoD) and Mobility-as-a-Service (MaaS). Numerous studies have been investigating these emerging modes, bringing them closer to the reality. For example, Lyft, Ford and Argo AI have collaborated and started operating autonomous ride-sharing services in Miami, U.S., with the goal to expand to Austin in 2021 [47].

Furthermore, an emerging mobility service, Urban Air Mobility (UAM), has gained increasing attention in recent years. The so-called "air taxi" provides on-demand service to transport passengers using electric vertical take-off and landing (eVTOL) aircrafts that travel point-to-point between urban infrastructures (e.g., roofs) or open spaces. It offers a safe and sustainable alternative to existing transportation modes [35]. As the transportation sector contributed 29% of the greenhouse gas emissions in 2019 (pre-COVID) and numerous time has been lost in congestion, UAM is shown to have the potential to contribute to a future with these problems alleviated [86].

The concept of UAM may be traced back to around 1917 when the first "flying car", Curtiss Autoplane, was invented by Glenn Curtiss [24] [51]. However, even though there existed a wide interest from both the industry (e.g., Ford) and the government, the flying car did not achieve commercial viability due to practical (e.g., regulatory) and technical issues (e.g., vehicle stability and safety) [24]. Later in the 1950s to 1980s, early UAM operations appeared: several companies provided scheduled helicopter services in major U.S. cities [24]. For instance, New York Airways provided passenger services in the New York City: a seven-minute trip from Manhattan to John F. Kennedy International Airport would only cost $56 in today's price [16]. However, this early UAM business eventually ceased operations under various obstacles: e.g., noise, financial burden, maintenance issues, and safety [16]. The company had accidents that caused deaths of both passengers and crew members [16].

Recent technology advancement has opened a new era for UAM, and the industry has been growing at an accelerating speed. The concept of "flying car" has several successful realizations in the industry: Joby Aviation, Lilium and EHang are one of the leading companies building and testing eVTOL aircrafts. With these models, many obstacles faced in the last century have been addressed. For example, the noise level produced by existing eVTOL models can be as low as a normal human conversation [20]; safety is improved with automated control systems to avoid human errors [30]; technological development in electrification helped reduce financial burden [19]. The day when UAM becomes a reality is not far away. In fact, Voom has operated UAM service in São Paulo, Mexico City and San Francisco Bay Area since 2016, but ceased operations due to COVID [59]. Joby Aviation has been preparing for an initial operation in 2024 [71].

However, as UAM is approaching its real-world realization in the near future, the system-wide impacts of UAM remain clear. First, the impacts of UAM on congestion and emission have not been fully understood. While UAM has been envisioned to be a sustainable alternative to existing transportation mode by utilizing the space of the third dimension and being powered by electricity, the potential impacts have not been systematically analyzed yet. How are different types of eVTOL fleet influencing the emission? How much can UAM help reduce road congestion, or will it exacerbate the current situation? Which types of business model have greater potential in reducing congestion and emission? Second, the impacts of UAM on mobility pattern also remain unknown. What is the size of the UAM market? Which trips and what kind of users are most likely to be attracted to UAM? How do different supply configurations affect the UAM market? It is critical to understand these potential impacts of UAM, as well as the associated uncertainties, in order to properly regulate the emerging UAM service and to promote a healthy market. Through rigorous analysis, the potential advantages and risks of UAM may be identified, and decisions may be made to maximize the potential benefits while minimizing the risks.

1.2 Thesis Objective and Contribution

This thesis focuses on analyzing the impacts of UAM on mobility pattern. Specifically, while existing literature provided valuable insights into UAM market size and demand characteristics, the specific market size by the trip characteristics (e.g., trip purpose) and the UAM user compositions has not been analyzed yet. Furthermore, the impacts of supply constraints on these demand characteristics remain unknown, including the impacts of capacity, accessibility, and pricing.

To achieve the above objective, this thesis proposes an agent-based simulation framework to comprehensively model UAM combining demand, supply, and their interactions at fine spatial and temporal levels. This enables the author to simulate realistic scenarios, explore impacts of supply under uncertainties and generate insights for planning applications with:

1. A demand-centric vertiport placement with realistic vertiport capacity generation;
2. Explicit UAM service operations that include rebalancing, charging and transition activities at vertiports;
3. A behaviorally sound representation of underlying decision-making process that

captures the switching behavior with the introduction of UAM.

1.3 Thesis Organization

This thesis is organized in the following way. Chapter 2 summarizes existing UAM literature. Chapter 3 presents the details of the UAM extension of SimMobility. Chapter 4 describes the simulation experiments. Chapter 5 shows the results and Chapter 6 discusses the key findings. Lastly, Chapter 7 concludes the thesis.

Chapter 2

Literature Review

With the recent leap of aviation and electrification technologies, there has been growing research in the use case of electric vertical take-off and landing (eVTOL) vehicles for transporting passengers. Booz Allen Hamilton investigated the market of air taxi, airport shuttle and air ambulance, and suggested that the first two have viable markets [42]. In addition to air taxi, Crown Consulting analyzed the market of air metro and found it to be more viable than air taxi in the near term [43]. Among the use cases, air taxi, which provides on-demand service for passengers and has been known as Urban Air Mobility (UAM), has received the most attention.

To better understand the future of urban environments with the presence of UAM, it is critical to consider: (i) the relationship of demand for this service to various supply-side factors (e.g., vertiport locations and designs, eVTOL characteristics, and service pricing); (ii) various obstacles hindering the UAM diffusion, both on the demand-side (e.g., public acceptance and rider experience) and on the supply-side (e.g., regulation, noise, safety, emission, and infrastructure); and (iii) the corresponding uncertainties. This section summarizes the existing literature pertaining to the UAM supply and demand.

2.1 UAM Supply

A UAM eVTOL Aircraft

The UAM industry has been developing rapidly, with the development of many models for the eVTOL aircrafts. Table 2.1 presents a non-exhaustive list of the technical specifications of existing eVTOL models. Existing models have a total number of seats between 2 to 7, a range between 35 km to 300 km, and a cruise speed between 110 km/h to 322 km/h.

As noted by [94], fast charging technology is critical for time and cost efficient UAM operations. Lilium reported that their aircrafts may be charged to 80% from zero in 15 minutes, and be fully charged in 30 minutes [97]. Archer indicated that for aircrafts serving missions in range of 20 to 40 miles, it would take on average 10 minutes to change for the next flight [70]. UberAIR suggested that frequent charging between flights is necessary to operate continuously for 3 hours on 25-mile missions before the battery is drained [84].

Table 2.1: Existing eVTOL Model Specifications (Non-exhaustive)

Model Name	Total Number of Seat	Range (km)	Cruise Speed (km/h)
ACS Aviation Z-300 [78]	2	300	222
CityAirbus NextGen [3]	4	80	120
Bell Nexus 4EX [81]	5	97	241
Lilium Jet [82]	7	250	280
Ehang 216 [29]	2	35	130
Volocopter VoloCity [89]	2	35	110
Wisk [91]	2	40	160
Archer Maker [79]	2	96	241
Autoflight V1500M [80]	4	250	200
Bartini [14]	4	150	300
Joby [11]	5	241	322

B UAM Operation

In addition to eVTOL aircraft design, existing literature on service operations has provided insights into pricing, mission profile, and operation efficiency.

Table 2.2 summarizes the service price literature, which shows a wide range between \$0.273/seat-km and \$6.84/seat-km. As a reference, according to the American Automobile Association (AAA), considering both operating and ownership costs, the average cost of owning a car ranges between ¢54.6/mile and ¢82.4/mile (\$0.339/km and \$0.511/km) [10]. The UberX cost per mile is around \$1/mile to \$2/mile (\$0.621/km to \$1.24/km), in addition to other fares, including base fare, cost per minute, etc. [44]. The more expensive UberBlack is on average twice the price of UberX [45]. Therefore, as also noted by Eric Allison, previous head of Uber Elevate, the long-term cost reported by Uber Elevate is comparable to the average car ownership cost [28]. On average, the industry projects a price comparable to UberBlack [19] [52]. High degree of uncertainty has been reported by [42], with a large portion coming from network efficiency, including utilization and cruise speed. Overall, automation, electrification, and increased occupancy by providing ridesharing service have been identified as the keys to reduce cost [19] [42] [52].

Table 2.2: Price Literature

Source	Price (\$/seat-km)
Uber Elevate Summit 2018 [28]	3.56 (at launch) 1.16 (near term) 0.273 (long term)
Lilium [52]	1.40
Archer [52]	2.05
Joby [52]	1.86
Wisk [19]	2.49 - 4.97
Booz Allen Hamilton [42]	3.88 - 6.84

Operation efficiency has also been widely studied by the literature. Researchers have explored systematic effect of operation characteristics, for example fleet size and fleet composition, and developed algorithms to improve UAM operation efficiency using optimization and simulation methods [5] [6] [15] [50] [53] [55] [64]. As eVTOLs are powered by electricity and generate zero emission when flying, UAM is promising to contribute to a sustainable future of urban mobility [2]. To evaluate this potential, emission has been examined in various studies. While UAM does have the potential to be more energy efficient, the literature suggests that energy consumption varies by distance and occupancy. Some studies have shown that UAM is only greener than internal combustion engine vehicles above a certain distance threshold and one of the major sources of energy consumption is hovering [18] [49].

C Vertiport Infrastructure

Infrastructures, specifically vertiports, are critical components of the UAM service. Numerous studies have explored vertiport layout designs for placing Final Approach and Take-Off (FATO) zones, gates and other facilities, based on available space at the selected sites [25] [65] [87] [88] [98]. Additionally, vertiport placement has been studied, and various approaches have been applied, including the followings:

1. Heuristic approaches based on regulation, operational requirements, and experts workshops [7] [63];

2. Systematic demand-based and Geographic Information System (GIS)-based approaches: e.g., k-means clustering algorithm [8] [33] [56] [76];

3. Optimization methods, that maximize revenue and ridership for the operator, or maximize travelers' benefit with regards to time and cost [26] [69] [90] [92];

4. Iterative approach that adjust to the demand under a constraint for the desired number of vertiports [72].

2.2 UAM Potential Demand

Public attitudes and perceptions have been widely recognized as the major obstacles to UAM implementation, including community backlash, visual and noise pollution, safety, privacy, and equity concerns [4] [22] [27] [42] [77] [95] [24]. Privacy concerns of both the UAM passengers and non-users have been raised: while the non-users are worried about being exposed and being seen from up in the air, the passengers expressed concerns about data privacy [42] [4] [77]. In addition, equity is one of the major barriers to public acceptance, as prices are likely to be higher than existing transportation modes and therefore impose affordability constraint for the general public [77] [24].

It is thus important to analyze the characteristics and size of potential UAM demand, which facilitates more informed decision-making, e.g., with regards to means of conquering the obstacles. In this section, the UAM demand literature is summarized by the following perspectives: (i) UAM demand characteristics; (ii) UAM market size.

A Demand Characteristics

Empirical studies have been conducted to understand the characteristics of UAM demand, characterizing the potential users of UAM. Socio-demographics, including income, age and education have been widely noted as important factors: e.g., high-income individuals have been identified as the potential users of UAM [4] [17] [38] [40] [42]. In addition, [75] suggested that variety-seekers are more likely to switch to UAM, characterized by higher income and having experienced delay in the past.

In addition to characterizing the UAM users, the literature has also suggested the potential UAM trip characteristics. [38] and [40] highlighted that UAM is most likely to be used for business purpose. On the other hand, based on the general population survey, [42] noted that long-distance recreational and airport access/egress are the most likely purposes of using UAM. Besides trip purpose, studies have also probed into the potential distance range of UAM trips. Some studies showed evidence of willingness to fly long-distance trips, either for recreation or commute [40] [42] [54]. On the other hand, [39] showed that, while UAM penetration rate is higher among the long-range trips, the majority of UAM trips are short-range less than 10 km. Lastly, modes of access to and egress from the vertiports have been examined in several studies. Riding or driving a personal vehicle, MoD service, and public transit have been noted as the most preferred mode for UAM access/egress trips [42] [67] [74] [92].

B Market Size

The potential UAM market size has been analyzed in multiple studies. As UAM has not become a reality, there exists no Revealed-Preference (RP) data, and Stated-Preference (SP) data is a useful tool to understand the user preferences. Among the researches focusing on UAM market analysis, some studies analyzed UAM market without SP data and the others used SP data to construct their demand models.

One group of studies analyzed UAM demand without UAM SP data. These studies based the analyses on existing data, e.g., travel survey data, and developed models with assumptions on the Value of Time (VOT). UAM operations and vertiport sizing are not under considerations in these studies. Table 2.3 summarizes their methodologies regarding demand model construction and infrastructure placement. Overall, these studies reported a UAM market penetration rate between nearly zero (0.001%) and 19%, showing great uncertainty [12] [13] [54] [58] [66] [76].

Table 2.3: UAM Market Size Literature Without UAM SP Data

Source	Location	Demand Model Description	Infrastructure Placement
[66]	7 U.S. metropolitan areas	Multinomial logit model estimated from travel survey data with generic coefficients	Selected conventional paved runways and existing helipads
[13]	Zurich	Multinomial logit model developed from travel diaries, and VOT for UAM is assumed to be the same as public transit	Not modeled (instead, assumed access time)
[12]	Zurich	Multinomial logit model developed from travel diaries, and VOT for UAM is assumed to be the same as public transit	Selected based on expertise of commuting demand
[58]	31 cities around the globe	Binary model that chooses UAM if willingness to pay (WTP) is higher than UAM cost; WTP is bsaed on recommendations by U.S. Department of Transportation	Vertiport distributed on grid-like network with varying density
[54]	Germany	With a gravity model, constructed a transport mode preference model to capture UAM demand based on opportunity cost	Selected from existing airfield based on runway performance of the potential aircrafts
[76]	North California, Washington D.C.	Conditional logit model for commute mode choice developed from travel survey, commuter origin/destination and community survey data, with generic coefficients	K-means clustering approach, based on commuter demand and income data

Another group of studies analyzed the potential UAM market based on SP data. The collected data are used to construct demand models, whose estimated parameter values are then used to extend existing base models that do not include the UAM alternative. Table 2.4 summarizes these studies' methodology regarding demand model construction, infrastructure placement, and whether or not fleet operation is modeled. Conditional logit model and incremental logit model have been used in the majority of these studies. Vertiports were selected by the previously mentioned methods in Chapter 2.1 Section C, and vertiport capacities were assumed to be unlimited. [63] [67] [68] [72] [74] Among these studies, [72] and [68] did not model the fleet operation, while the others used MATSim with the UAM-extension developed by [73]. While some components of fleet operation, e.g., charging and rebalancing, were still missing, these studies with agent-based simulations shared valuable insights on market penetration in various locations, predicting a potential UAM penetration between 0.14% to 4% [63] [67] [74].

Table 2.4: UAM Market Size Literature Based On UAM SP Data

Source	Location	Demand Model Description	Infrastructure Placement	Fleet Operation (Y/N)
[72]	North California	Conditional logit model; UAM constants adopted from [17]	Selected iteratively, adjusting to demand	N
[68]	Upper Bavaria	Incremental logit model with train as the reference mode; UAM sensitivity adopted from [38]	Selected from points of interest	N
[67]	Upper Bavaria	Incremental logit model with train as the reference mode; UAM sensitivity adopted from [38]	Selected through four workshops with experts	Y
[74]	Sioux Falls	Mode choice only dependent on VOT (method of determining VOT not specified)	Placed near transport nodes, points of interest, and existing helipads	Y
[63]	Upper Bavaria	Incremental logit model with train as the reference mode; UAM sensitivity adopted from [38]	Selected through four workshops with experts	Y

2.3 Thesis Contribution

While the literature has provided insights into the characteristics of potential UAM demand, several questions regarding the impacts of UAM on mobility pattern have not yet been investigated. First, analysis of demand characteristics, e.g., user composition by income and market penetration by different trip characteristics, remains a research gap. Second, the impacts of supply on various demand characteristics, with respect to both users and trips, are also not fully understood. However, identifying these impacts on mobility pattern and the effects of supply configurations are important for deriving policy implications to promote a healthy UAM market.

Therefore, this thesis aims to contribute to the UAM literature by using the state-of-the-art simulation platform, SimMobility to analyze the potential demand of UAM. A comprehensive UAM model is developed combining demand, supply, and their interactions at fine spatial and temporal levels. As compared to existing agent-based models analyzing potential UAM demand, the approach applied by this thesis has the following strengths:

1. A demand-centric vertiport placements procedure with realistic vertiport capacity generation;

2. Explicit UAM service operations that include rebalancing, charging, and transition activities at vertiports;

3. A behaviorally sound representation of underlying decision-making process that captures the switching behavior with the introduction of UAM.

Chapter 3

Simulation Laboratory

In this thesis, the state-of-the-art simulation laboratory, SimMobility, has been used to analyze the potential UAM demand. SimMobility is a high-fidelity, integrated agent- and activity-based model that mimics the real-world with three simulators as shown in Figure 3-1. These simulators model different time scales: (i) the short-term performs microscopic traffic simulations at the fraction of seconds (e.g., behavioral decisions such as acceleration and lane changing); (ii) the mid-term simulates activity and travel decisions from plans to actions on an average day; (iii) the long-term simulates longer term decisions such as residential location, work location, car ownership, and the monthly and yearly dynamics (e.g., in the housing market) [1].

The SimMobility mid-term component is used in this thesis and expanded to comprehensively simulate the introduction of UAM from three aspects: demand, supply, and their interactions. Figure 3-2 shows the structure of SimMobility mid-term with three modules: (i) the Pre-day module simulates agents' daily mobility decisions and yields a daily activity travel plan for each individual, based on an Activity-Based Model (ABM) system; (ii) the Within-day module simulates agents' execution behavior of the plans; (iii) the Supply module simulates the traffic movement at fine spatial and temporal scales. Lastly, demand-supply interactions are modeled through the iterative day-to-day and within-day learning modules in SimMobility [93].

In this section, the UAM simulation laboratory is described by the modeling of demand, supply, and the demand-supply interactions.

Figure 3-1: SimMobility Framework [57]

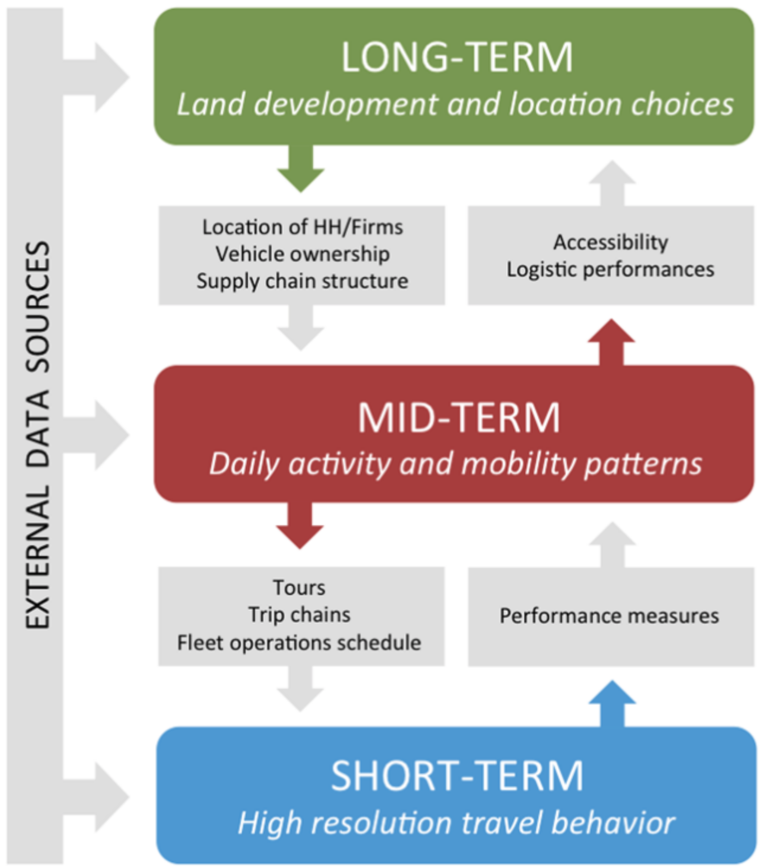
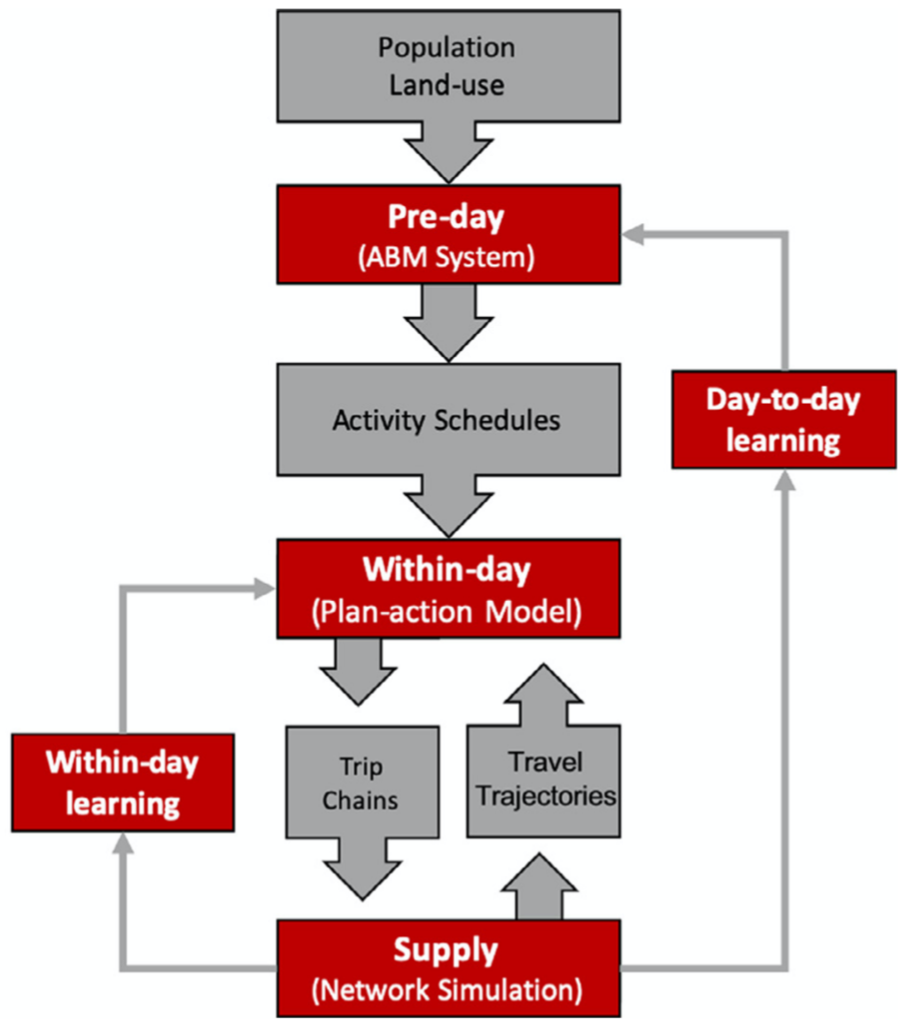


Figure 3-2: SimMobility Mid-term Simulation Flowchart [60]



3.1 Demand

The SimMobility Pre-day and Within-day modules have been extended to model UAM demand with a behaviorally sound approach that enables the modeling of: (i) access/egress modes to/from the vertiports and (ii) destination change with the presence of UAM.

A Pre-day

The SimMobility Pre-day module simulates daily activity schedule (DAS) for individuals in the population, based on an ABM system with hierarchical choice models as shown in Figure 3-3. Lower-level decisions are conditioned on higher-level decisions (solid arrows), and higher-level models include inclusive values from lower-level models (dashed arrows). There are three major levels:

1. **The day pattern level** constructs type, number and sequence of tours, as well as availability and purposes of intermediate stops.

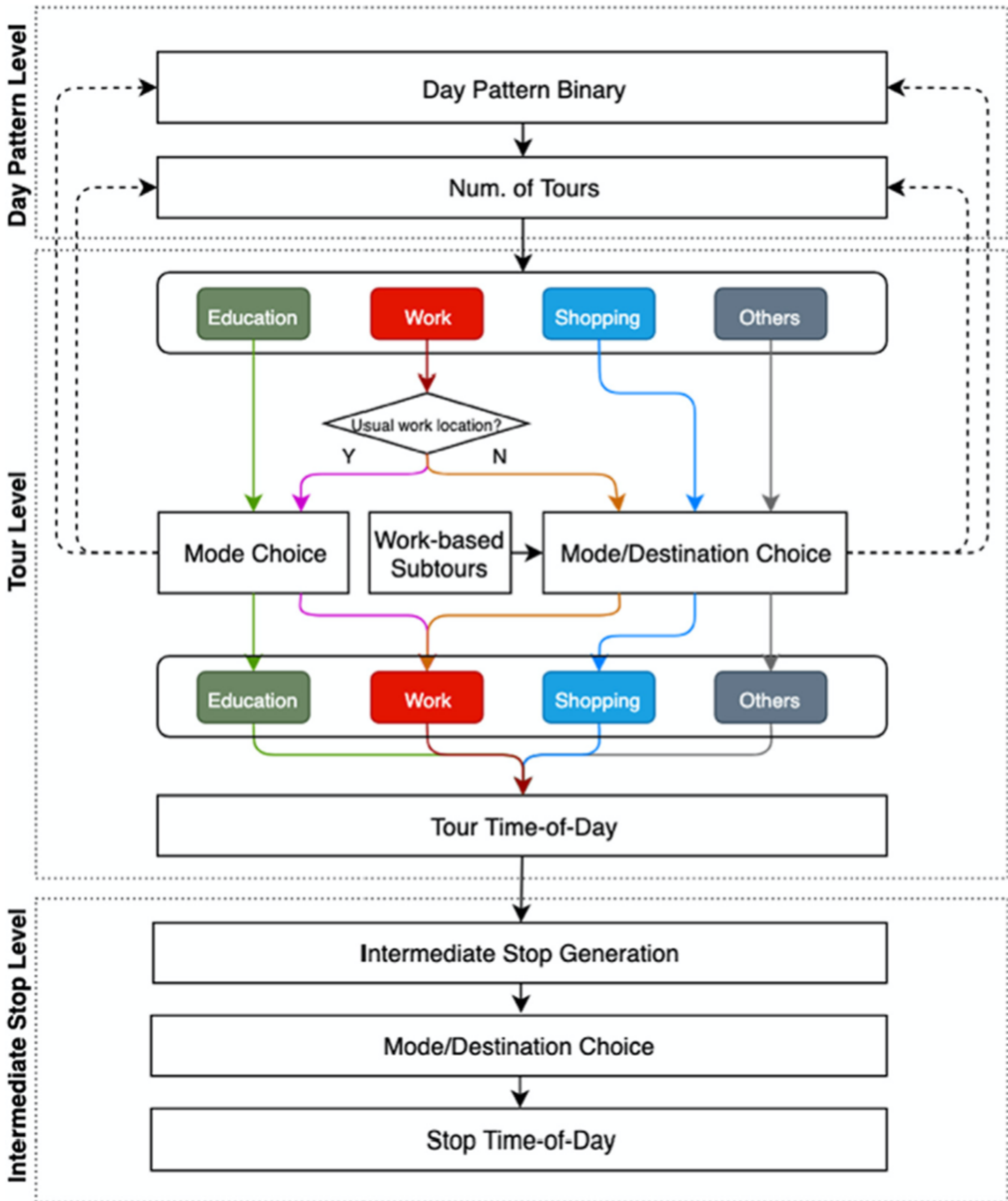
2. **The tour level** models choices of tour travel mode, destination, and time of day. The binary decision of whether to travel to usual work location or not is also included. In addition, work-based subtours are modeled at this level.

3. **The intermediate stop level** generates the sequence and characteristics of the stops before or after the primary activities, and simulates the decisions regarding number, travel mode, destination, and travel time of these stops.

Simulation of the ABM generates a DAS for every individual in the population. [62]

With regards to travel modes included in the ABM, the simulations performed in this thesis consider the following travel modes before the introduction of UAM: private bus (i.e., shuttle bus and school bus), Public Transit (PT), drive-alone, carpooling with two people, carpooling with three or more people, walk, bike, motor, taxi, and MoD. The carpooling alternatives do not differentiate between drivers and passengers. For PT, three access/egress modes are considered: walk, drive-alone or MoD. Four

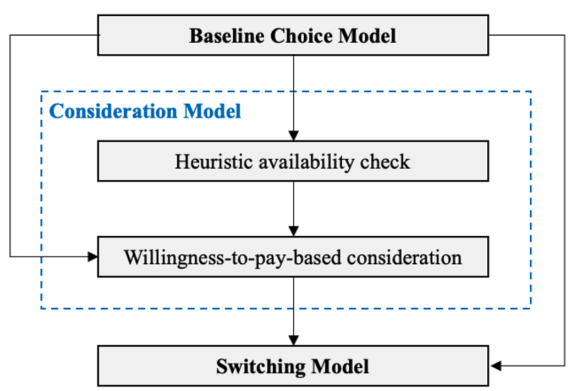
Figure 3-3: SimMobility Pre-day Model System [60]



types of activities are included: work, education, shop, and others. As shown in Figure 3-3, SimMobility Pre-day has two types of mode choice models: mode choice models and mode-destination choice models. The tour level consists of both of these models, while the intermediate stop level only has mode-destination choice model. [93] In the following text, all these models involving mode choice are referred to as the *baseline choice models*. To model the mode choice behavior with UAM, two additional models have been developed: (i) a *consideration model* and (ii) a *switching model*. Figure 3-4 presents the framework of the UAM Pre-day demand model.

The following UAM alternatives are considered in the *consideration model* and *switching model*: *Park & Fly*, *Kiss & Fly*, *MoD & Fly* and *Public Transit/Walk & Fly*. PT and walk modes are combined as sustainable modes not based on cars. The number of UAM alternatives differs in mode choice models and mode-destination choice models. In mode choice models, there are four UAM alternatives with different access/egress modes. In mode-destination choice models, the UAM alternatives are combinations of access/egress modes and the destination zones.

Figure 3-4: UAM Pre-day Demand Model



The *consideration model* simulates agents' decisions of whether to consider UAM or not based on two submodules: (i) heuristic availability check; (ii) willingness-to-pay-based consideration.

With the heuristic availability check submodule, an initial filtering based on heuristics is performed for the UAM alternatives, with different checks for the tour level and intermediate stop level models. For the tour level models, the following checks are applied:

1. If the chosen non-UAM mode from the *baseline choice models* is walk or bike, the travel time saving must be positive for UAM alternatives to be considered.

2. For work and education tours, if the chosen non-UAM mode is walk, only *Public Transit/Walk & Fly* will be considered, with additional checks as the followings. If the current one-way tour distance is less than 0.8 km (0.5 mile), UAM is not considered. The U.S. Federal Highway Administration suggests that most individuals travel 0.25 to 0.5 mile to a transit stop [36]. Therefore, it is assumed in this thesis that people are more willing to walk for such short-distance trips than using UAM. Furthermore, if one of the access/egress trip to/from the vertiport is greater than 0.8 km, UAM is also not considered.

3. For work and education tours, if the chosen non-UAM mode is bike, the heuristic checks used above for walk apply as well with a distance threshold of 2.5 km, which is 7.5-minute biking with a speed of 20 km/h.

4. For shop and other types of tours, the attractiveness of the destination must be greater than the chosen one, for the UAM alternative to be considered. In other words, destination change with UAM is only considered when the new destination is more attractive. The measure of attractiveness includes number of employment, population, and zone area.

5. UAM and the access/egress mode must be available. For UAM service availability, the origin and destination must be connected by the UAM vertiports. Operation hours have not been considered in this thesis.

Similarly, the intermediate stop level models check the following heuristics, regardless of the stop purpose:

1. If the chosen non-UAM mode from the *baseline choice models* is walk or bike, the travel time saving must be positive for UAM alternatives to be considered.

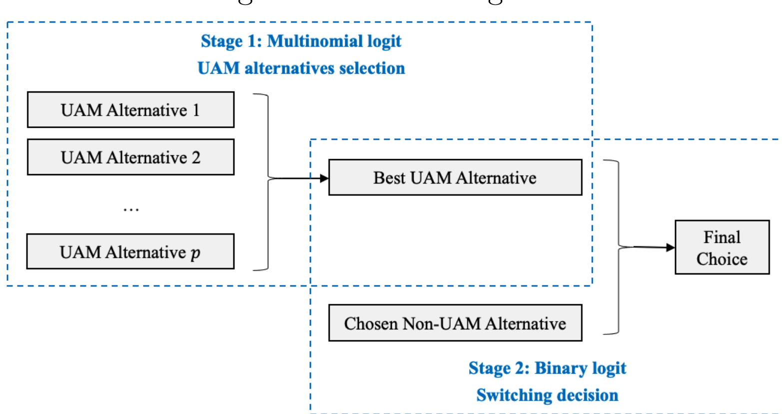
2. The attractiveness of the destination must be greater than the chosen one for the UAM alternative to be considered.

3. UAM and the access/egress mode must be available.

The willingness-to-pay-based step computes the willingness to pay (WTP) for UAM alternatives against the chosen non-UAM alternative from the *baseline choice model*, based on travel time saving and extra cost. Only UAM alternatives that passed heuristics availability check and have nonnegative WTP are available in the *switching model*.

Lastly, the *switching model* is applied to model agents' decision of whether to switch to UAM or not with two stages of decision, as shown in Figure 3-5. Stage 1 is a multinomial logit model that selects the best option out of all UAM alternatives. Figure 3-5 shows a situation when there are p UAM alternatives to select from. The UAM utilities are in WTP space, for which the VOT is individual-specific and calibrated for the *baseline choice model* against travel diary data. Equation 3.1 presents the utility of UAM alternative i for individual n. Stage 2 is a binary logit model that mimics a switching decision: either switch to the best UAM alternative, or do not switch and remain with the chosen non-UAM alternative. The utility for non-switching is normalized to 0, and Equation 3.1 is used again for computing utility of the switching alternative.

Figure 3-5: Switching Model



$$
\begin{aligned}
U_{i,n} = &-ExtraCost_{i,n} + VOT_n \times TimeSaving_{i,n} \\
&+ \beta_0^{SM} + \beta_{age\_46\_55}^{SM} D_n^{age\_46\_55} + \beta_{age\_56\_65}^{SM} D_n^{age\_56\_65} + \beta_{senior}^{SM} D_n^{senior} \\
&+ \beta_{curr\_PT\_carpool}^{SM} D_n^{curr\_PT\_carpool} + \beta_{curr\_walk\_bike}^{SM} D_n^{curr\_walk\_bike} \\
&+ \beta_{high\_inc}^{SM} D_n^{high\_inc} + \epsilon_{i,n}
\end{aligned}
$$

$where$

$VOT_n = VOT$ of individual n

$ExtraCost_{i,n} =$ extra cost of UAM alternative i for individual n, compared to chosen non-UAM alternative, USD

$TimeSaving_{i,n} =$ perceived time saving of UAM alternative i for individual n, compared to chosen non-UAM alternative, hr

$\beta^{SM} =$ coefficients of constant, socio-demographic, and lagged variables

$D_n^{age\_46\_55} = 1$ if individual n's age is between 46 and 55, otherwise 0

$D_n^{age\_56\_65} = 1$ if individual n's age is between 56 and 65, otherwise 0

$D_n^{senior} = 1$ if individual n is older than 65, otherwise 0

$D_n^{curr\_PT\_carpool} = 1$ if current chosen non-UAM mode is PT/carpool, otherwise 0

$D_n^{curr\_walk\_bike} = 1$ if current chosen non-UAM mode is walk/bike, otherwise 0

$D_n^{high\_inc} = 1$ if monthly household income > 8600 USD, otherwise 0

$\epsilon_{i,n} =$ error term of the utility of UAM alternative i for individual n

(3.1)

To compute the utility, several components are considered, for which the parameters are adopted from existing studies, including [38], [75] and [34]. Table 3.1 summarizes the original parameter estimates reported by these studies.

Constants, socio-demographic variables and lagged variables on chosen non-UAM mode are included. The coefficients are adopted from [38] by converting to WTP space. The threshold of having high-income has been converted with an exchange rate of 1 EUR = 1.2285 USD in February to April 2018 when the survey was conducted [32]. In addition, while [38] does not include this, a lagged variable on choosing carpool in the *baseline choice model* is included in the *switching model* utility, and the parameter is assumed to be the same as PT.

Extra cost is directly computed, and the UAM cost includes cost of access, in-flight, and egress trips. For perceived time saving, the total UAM travel time is computed as a weighted summation of access, waiting, in-flight, and egress times, and the weights are adopted from [75] and [34]. To compute the weights, the VOTs of different UAM travel components reported by [75] are scaled by fixing flight time scale as 1. As [75] does not include wait time VOT, perceived-actual wait time ratio around 1.25 for PT, found by [34], is used. Converting this ratio from PT (a non-UAM mode) to UAM, i.e., $1.25 \times \frac{20.8}{14.0} = 1.87$ is the UAM wait time scale used. Table 3.2 summarizes the parameter values used in the *switching model*.

Table 3.1: Parameter Values Reported by Studies

Source	Parameter	Value
[38]	travel cost	-0.470
	ASC	-2.92
	age 46 - 55	-1.12
	age 56 - 65	-1.12
	age > 65	-1.74
	current means of transport: PT	-1.50
	current means of transport: walk/bike	-1.99
	high income (monthly household income > €7000/month)	0.790
[75]	UAM access VOT	26.2
	UAM egress VOT	34.2
	flight VOT	20.8
	in-vehicle travel time VOT (non-UAM modes)	14.0
[34]	PT perceived-actual wait time ratio	1.25

The *switching model* compares the WTP for the time saving, given that a non-UAM alternative has been chosen, and simulates a binary decision. It is a behaviorally sound process that mimics the switching behavior individuals may have when UAM enters the market: individuals compare UAM with the travel modes that they are already using, and decide to switch to UAM or not. Additionally, since UAM alternatives consist of combinations of destination and access/egress modes, the Pre-day

Table 3.2: Switching Model Parameters

Parameter	Value
ASC	-6.21
age 46 - 55	-2.38
age 56 - 65	-2.38
age $>$ 65	-3.70
chosen non-UAM mode: PT/carpool	-3.19
chosen non-UAM mode: walk/bike	-4.23
high income (monthly household income $>$ 8600 USD/month)	1.68
access time scale	1.26
egress time scale	1.64
wait time scale	1.87
flight time scale	1.00

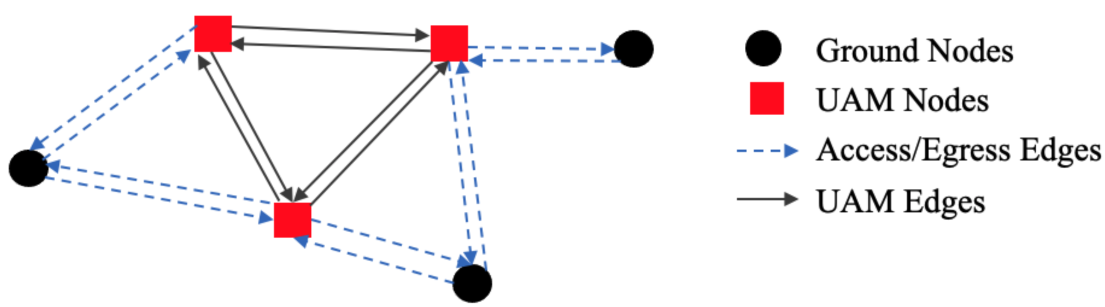
demand model enables change of destination with UAM. This is a realistic representation as people may reconsider their destinations now that they can travel further in less time with UAM.

B Within-day

While Pre-day simulates agents' decisions on daily activity travel plans, Within-day simulates how agents execute the plans, e.g., route choice and departure time choice. The UAM extension has been implemented for the route choice model, including the construction of UAM network and paths. The UAM network integrates the ground road network with the vertiports, as shown in Figure 3-6. Two types of nodes are present in the UAM network: ground nodes and UAM nodes. A UAM node represents a small area with several vertiports nearby each other. This notion is also illustrated later in Chapter 4 Figure 4-6. For a certain UAM trip, the origin and destination are ground nodes. There are three types of edges: access edge from a ground node to a UAM node, UAM edge between UAM nodes, and egress edge from a UAM node to a ground node. It has been assumed that all vertiport pairs within the eVTOL maximum range are connected. The range differ by scenario and may be found in Table 4.1.

K-shortest paths that traverse origin/destination pairs among the ground nodes are computed based on the UAM network, and consist of three edges: access, UAM, and egress edges. In this thesis, k has been set to 5. These paths are computed prior to the Within-day simulation and are used during the simulation for performing route choice. As UAM and PT are both modes whose access and egress trips considerably affect the agent's decisions, UAM route choice is modeled by the existing SimMobility PT route choice model.

Figure 3-6: Integration of Ground Network with UAM Vertiports



For UAM access/egress modes, agents decide a high-level preference in Pre-day and determine the specific modes in Within-day. When the chosen access/egress mode from Pre-day is found to be infeasible in Within-day, a heuristic preference is applied and agents attempt to use the next preferrable mode. For instance, for an agent attempting to drive alone for the egress trip, if the car is not parked nearby the destination vertiport, the agent will use MoD instead. Only determining a high-level preference at Pre-day aligns with the decision-making process in reality, where day travel plans are subject to changes during execution.

3.2 Supply

To be able to simulate the on-demand UAM service, a controller has been developed for SimMobility with a high-level design shown in Figure 3-7. The controller operates the UAM service and is capable of request matching, aircrafts' states tracking and scheduling, queue managing, and rebalancing.

Upon request, the controller matches UAM passenger trips with available aircrafts at the origin vertiports immediately. At each time frame, new and unmatched requests are processed by their requesting times. Trips that could not be assigned an aircraft remain in the queue of requests, and the waiting times of the passengers are tracked. The trips may be either solo or pooled based on controller configurations, and reservation is allowed. Several considerations are taken into account to determine whether aircrafts are eligible for matching requests: trip length, current amount of charge, distance from the request's origin vertiport, aircraft capacity, and whether trips have been assigned. The eligible aircraft that can serve the request in the least amount of time is assigned to the request.

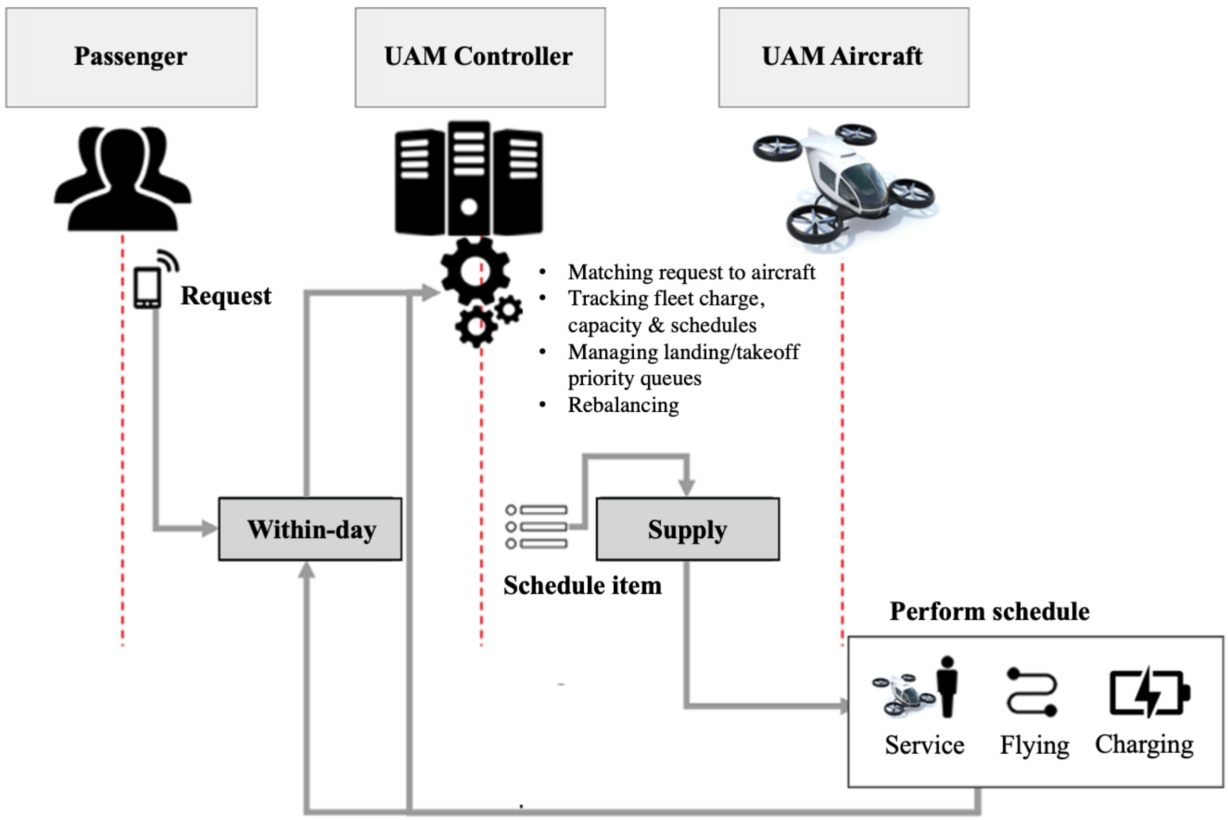
Aircrafts states, including charging level and seat capacity, are tracked by the controller. Charging level is critical to track to allow for realistic simulations that avoid situations when battery-deficient aircrafts are serving passengers. In addition, it is also essential for scheduling purpose. Tracking seat capacity, on the other hand, enables modeling of the pooled UAM trips. The aircrafts are also tracked for whether the current missions are completed, for which the next mission will be scheduled or they remain idle.

The controller schedules missions for the aircrafts. In addition to assigning aircrafts for take-off, landing, in-flight and taxiing, the controller explicitly models the transition into and between gates and FATOs, tracking the aircrafts' waiting time for available space. This feature thus captures the capacity constraint at the vertiports. For example, hovering phase that an aircraft waits for available FATOs to land is modeled, which is important to track for safety consideration. Rebalancing is also implemented to proactively serve demand. The aircrafts without any scheduled item are sent to vertiports that served the most recent requests.

Lastly, the use of FATOs and gates are managed by queues. The queue for using gates, regardless of arriving or departing aircrafts, is first-in-first-out. However, the queue for using FATOs is further enhanced to priority queue to improve efficiency and safety. It prioritizes hovering aircrafts with low charge to use the FATOs first to land.

For additional information on the UAM controller, readers may refer to [96].

Figure 3-7: UAM Service Controller



3.3 Demand-Supply Interactions

Demand and supply interact with each other. Under a certain supply configuration, individuals learn about the travel attributes and adjust their decisions after each day of travel. In SimMobility, this learning process is captured by the day-to-day learning module, with which the Pre-day, Within-day, and Supply modules are simulated iteratively until equilibrium. In the UAM extension, both passengers and service providers perform day-to-day learning.

For passengers, in addition to the learning of travel time and cost of ground transportation modes, two attributes are learned for UAM. First, UAM trip total passenger waiting time is learned for Pre-day *baseline choice models* as an aggregated zone-to-zone attribute. It is defined as the total time spent after arriving at the gate for boarding and before deboarding at destination, except for the flight duration. Therefore, time spent in the aircraft waiting for available FATO to take off or land is also included. Second, the time passengers expect to submit their requests in advance to avoid waiting at the vertiports is also learned, and is used during supply simulation. This attribute is vertiport-specific and varies by time of day, as different vertiports experience different levels of congestion in different times of day (AM-peak vs. off-peak vs. PM-peak).

For the service provider, operational parameters are learned for efficient fleet management. The vertiport-specific expected hovering time is learned for charging and scheduling purposes. It is the expected time an arriving aircraft has to wait for an available FATO for landing, and it is critical to track for safety. In addition, time that aircrafts with matched trips spent waiting for passengers to arrive is also learned to avoid unnecessary resource consumption at the vertiports: aircrafts waiting for passengers to arrive occupy the gate, while the facility may be used for other purposes (e.g., for other aircrafts whose passengers have arrived to load passengers and prepare for taking off). This is also a vertiport-specific value.

Day-to-day learning involves an iterative simulation process of both demand and supply. An equilibrium state is considered to be reached when the change in total passenger waiting time is negligibly small. More details may be found in [96].

Chapter 4

Simulation Experiments

The simulation laboratory has been applied to study the potential UAM demand in two selected prototype cities, which are representative cities of those with similar road network, public transit network, land use, and population characteristics [61]. For both cities, three UAM scenarios are simulated to analyze the effects of supply on potential UAM demand, including capacity, accessibility, and pricing. Uncertainty analyses are performed for all scenarios.

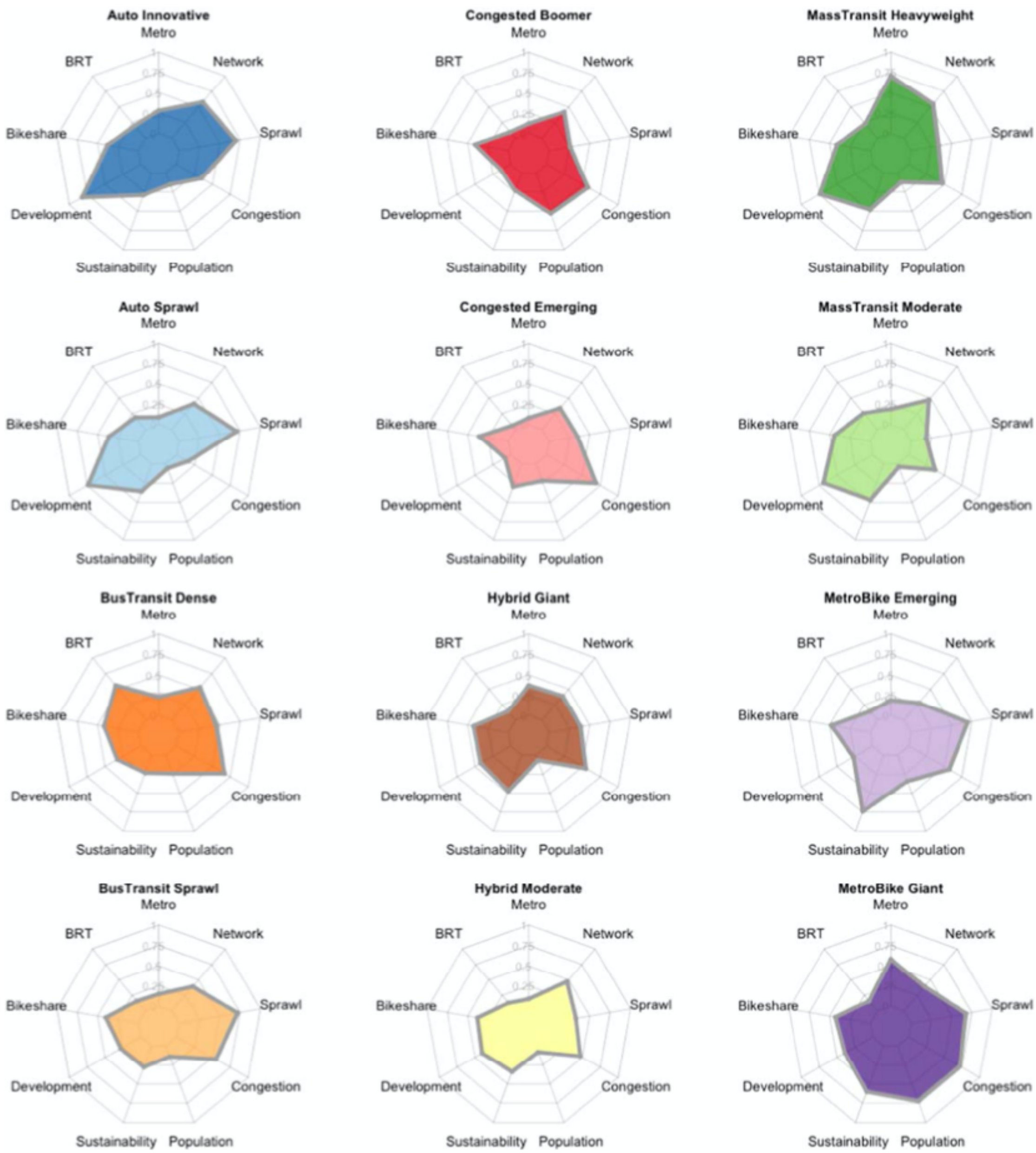
4.1 Study Area

[61] clustered major cities worldwide into 12 typologies based on economic, demographic, urban form, mobility, and environmental indicators. Figure 4-1 shows the spider plots of the typology profiles across nine factors.

The potential demand of UAM service is studied in two real North American cities that belong to distinct typologies: Auto Innovative (AI) and Auto Sprawl (AS). Both types of cities are highly industrialized and car-driven, but AI cities have more extensive transit systems [61]. Road network, public transit, land use, and population data were collected and processed to construct the prototype city databases for SimMobility simulations, using the pipeline developed by [83].

In this thesis, the selected real cities will be referred to by their prototypical names, AI and AS, due to confidential reasons. The metropolitan areas of the two cities are

Figure 4-1: Spider Plots of Typology Profiles [61]



studied. In AI, there is one major city at the center of the study area, around which cities are sporadically distributed, and becomes more rural toward the edge. On the other hand, in AS, there are two major cities in the area, one at the North end and one at the South end. Compared to AS, AI has higher income distribution and higher congestion level.

The baseline model without UAM has been calibrated with individual-specific VOT, against available travel diary data. Calibration items include average number of daily trips per agent, mode share, activity pattern, trips by time of day, and distance. It has been assumed that the agents' VOTs follow lognormal distributions, whose means differ by income and activity type as suggested by [85]. The simulated average number of daily trips per person are respectively 2.60 and 2.81 for AI and AS, while the travel diary datasets indicate 2.59 and 2.94 for AI and AS. Figure 4-2, Figure 4-3, Figure 4-4, and Figure 4-5 show the validation results, which suggest that the baseline model reasonably replicates the travel pattern of the two prototype cities.

Figure 4-2: Trip Mode Share Validation

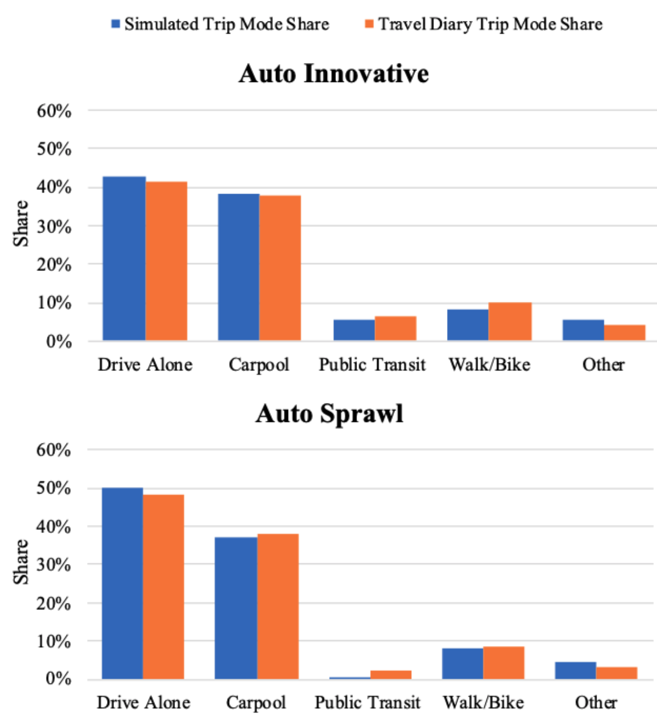


Figure 4-3: Trip Acitivity Pattern Validation

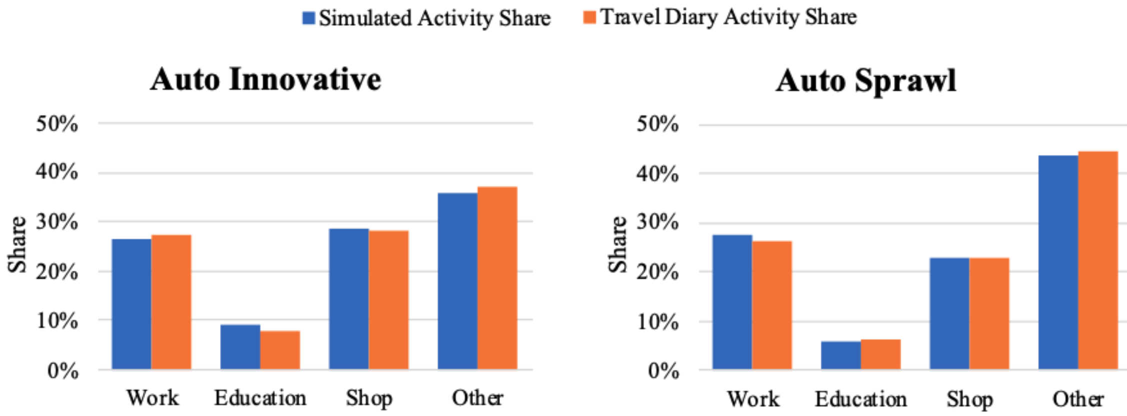


Figure 4-4: Trip Time of Day Validation

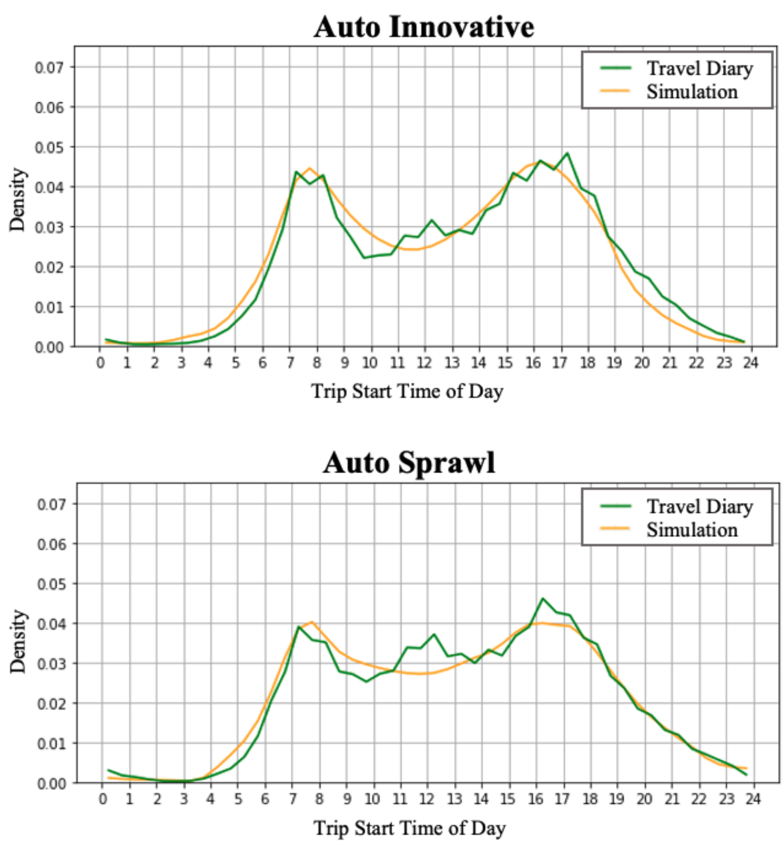
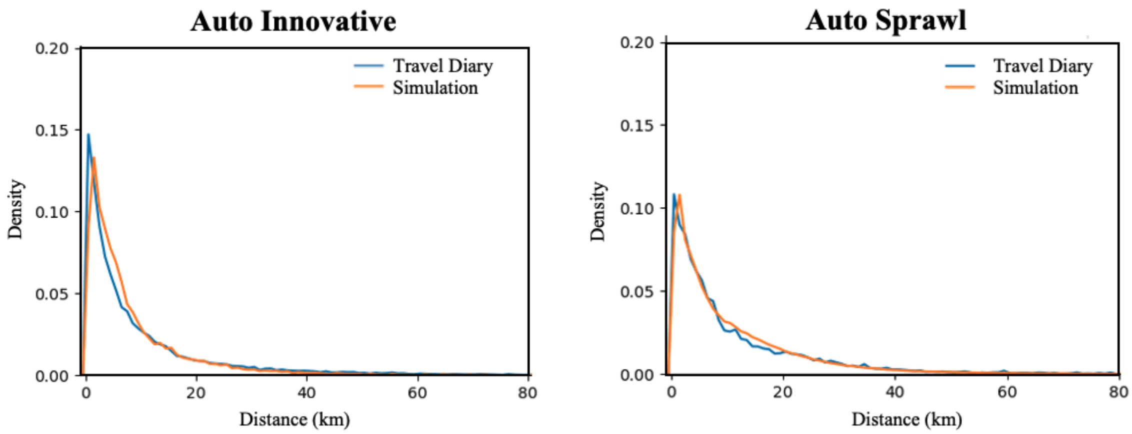


Figure 4-5: Trip Distance Distirbution Validation



4.2 Supply Configurations

This section summarizes the experiment setups regarding supply configurations, including vertiport placement and capacity generation, charging profile development, and fleet size determination.

As accessibility is a critical component of scenario analysis, it is necessary to define an accessibility measure for scenario designs. It is defined as the following: the percentage of population covered by 15-minute isochrones (driving) of the vertiports. In other words, it is the percentage of population who can reach a nearby vertiport in 15 minutes by driving. The specific percentages vary across scenarios as shown in Table 4.1. To place a set of vertiports that aligns with the scenario design, the following procedure has been applied to iteratively select the locations based on real geography, which follows a hierarchy from selecting potential high demand area to UAM node and to vertiport, as shown in Figure 4-6:

1. Select potential high demand areas based on income and commute time (home to work) data from City-Data and IndexMundi [23] [48].

2. Select UAM nodes inside the potential high demand areas. UAM nodes, as introduced in Chapter 3 Section B, are nodes with densely located vertiports.

3. Within the area defined by UAM nodes, select the exact vertiport(s) locations from the buildings, open space, commercial centers, distribution centers, and existing airports.

4. Run SimMobility to find passenger trip demand of each UAM node. Generate 15-minute isochrones (driving) for the selected vertiports and compute percent of population covered by the isochrones. The isochrones are generated using the QGIS plug-in tool openrouteservice (ORS) [37].

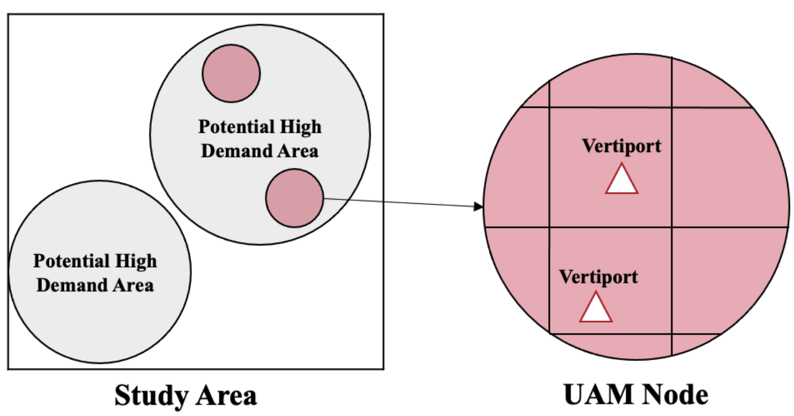
5. Compare the percentage of population covered against the accessibility measure pre-determined for the scenario:

   (a) If lower than the measure, add additional UAM node(s) and, if necessary, select additional potential high demand area(s).

   (b) If the percentage is higher, remove UAM node(s) with low demand.

6. Repeat step 3 to step 5 until the accessibility measure is matched.

Figure 4-6: UAM Vertiport Selection Hierarchy



Based on this approach and the scenario designs shown in Table 4.1, 23 vertiports are selected for AI and 19 for AS for the at-launch and near-term scenarios. For the long-term scenario, respectively 61 and 56 vertiports are selected for AI and AS. Spatially, in AI, the vertiports are densely located nearby the center major city, with some sporadically distributed in the suburban and rural areas. On the contrary, AS has two major cities around which vertiports are concentrated. Therefore, as compared to AS, AI has a higher density of vertiports near the major city.

Capacity, specifically the number of gates and FATOs, is generated for the selected vertiports. The vertiport designs shown in Figure 4-7 are used and are proposed by [87]. The layouts have number of FATOs ranging between 3 and 6, and number of gates between 9 and 16. Based on the actual space available on the selected sites, either 500 ft x 200 ft or 300 ft x 300 ft design is used. Furthermore, whether to use satellite or linear topology is adjusted to the simulation results to satisfy different types of vertiport needs. For example, for vertiports that have high average aircraft waiting time for available gates, the layouts with a higher number of gates are used; however, for vertiports with high average hovering time, designs with a larger number of FATOs are then used. Therefore, capacities are also generated iteratively based on controller simulation results to meet the UAM fleet traffic.

Lastly, it is assumed that aircrafts are all eVTOLs and may charge at the gates. A charging profile has been developed to model their state of charge. Lilium reported being able to charge to 80% from zero in 15 minutes and be fully charged in 30 minutes [97]. Assuming maximum range of 250 km for a Lilium eVTOL, and that the amount of charge is proportional to travel range, a profile is developed as shown in Figure 4-8 as a power function [82].

Lastly, fleet size is learned throughout the simulations. Various fleet sizes are experimented for a given demand, and the best one is selected for the day-to-day learning, based on average total passenger waiting time and aircrafts hovering time. In this thesis, it has been assumed that the fleet is homogeneous. As [50] suggested that fleet size has more impacts on operation efficiency than fleet composition, heterogeneous fleet has not been tested, but may be investigated in the future.

4.3 Scenario Design

Three scenarios are studied: at-launch, near-term and long-term. Capacity, accessibility and pricing are varied across the scenarios. For all scenarios, it is assumed that

Figure 4-7: Vertiport Layout Design [87]

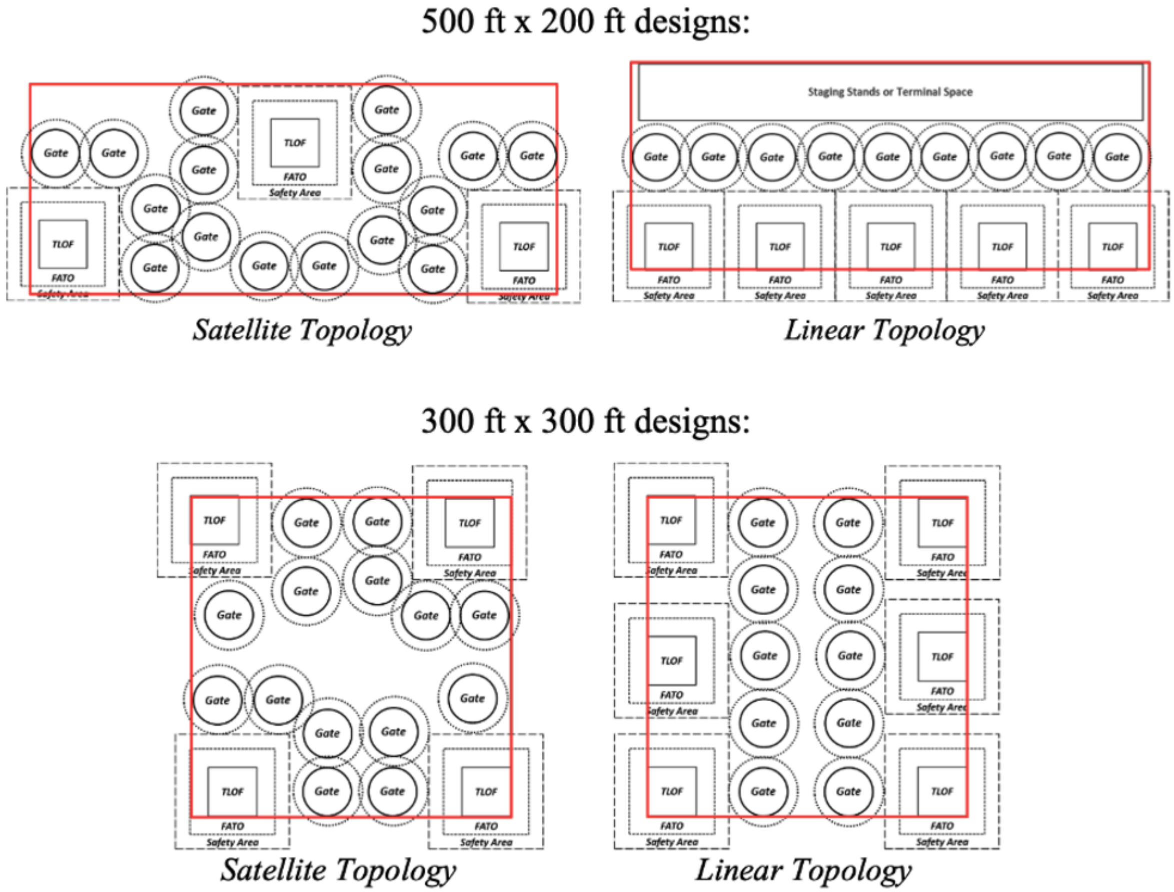
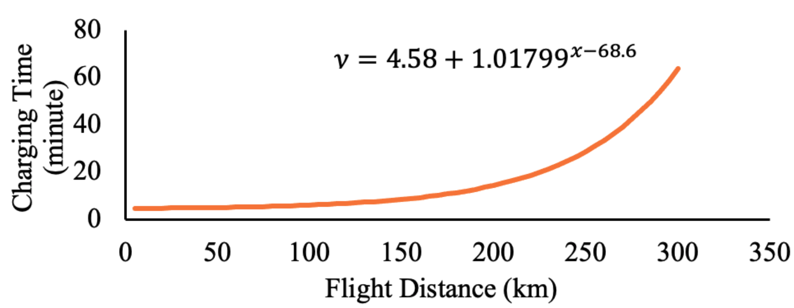


Figure 4-8: Charging Profile



the aircrafts have a speed of 200 km/h and range of 250 km, the same as AutoFlight V1500 [80]. As safety has been shown to be a major concern, aircrafts are assumed to be piloted with three passenger seats available [42] [80]. Based on estimates from [42] for 4-seater eVTOL, the price is assumed to be \$4.52/seat-km, and is reduced by 60% in the long-term. Table 4.1 summarizes the three scenario designs.

In at-launch scenario, the accessibility measure is lower, and the capacity is also limited to only one vertiport per UAM node. This mimics the scenario when UAM just enters the market, and numerous constraints are still in place, e.g., regulation and cost. In the near-term scenario, the capacity constraint is lifted by assuming that the average waiting time at vertiports is 2.5 minutes. This could be caused by increased number of vertiports per UAM node, or more efficient operations by the suppliers. Lastly, in the long-term scenario, it is assumed that supply constraints are futhered released. Therefore, along with the reduced price, it is assumed that vertiports are more wide-spread, therefore having a higher accessibility measure.

Table 4.1: Scenario Designs

<table>
<tr><th>UAM Scenario</th><th>Unit Price ($/seat-km)</th><th>Accessibility Measure*</th><th>Capacity</th></tr>
<tr><td>At-launch</td><td rowspan="2">4.52</td><td rowspan="2">70%</td><td>1 vertiport/UAM node</td></tr>
<tr><td>Near-term</td><td rowspan="2">(Assume 2.5' waiting time)</td></tr>
<tr><td>Long-term</td><td>1.81</td><td>90%</td></tr>
</table>

*Note: %population covered by 15-minute isochrones (by driving) of selected vertiports

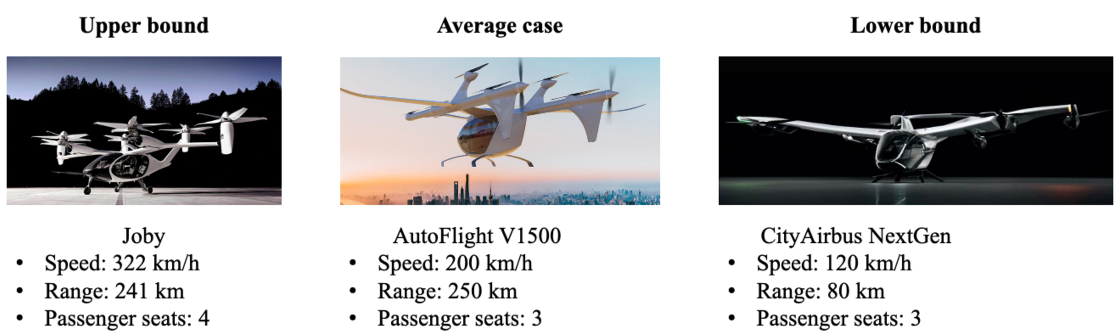
Uncertainty analyses are performed for all scenarios, resulting in sub-scenarios: upper bound, average case (no uncertainties), and lower bound. Uncertainties of demand model parameters are based on reported standard errors from [38] and [75] to account for the variations in unobserved factors, e.g., public perception.

The uncertainties of the supply-side are accounted for by varying aircraft type and price. The upper bound assumes fast aircrafts with 322 km/h speed, 241 km range and four passenger seats, based on Joby [11]. As estimated by [42], it is assumed that these piloted 5-seater aircrafts have unit price of \$3.88/seat-km. The lower bound assumes slow aircrafts with 120 km/h speed, 80 km range and three passenger seats, based on CityAirbus NextGen [3]. A unit price of \$4.52/seat-km is assumed for these 4-seaters based on estimate from [42]. In addition, as [42] reported 50% uncertainty in price, the upper bound price is reduced by 50% and lower bound price is increased by 50% for the corresponding aircraft type. Finally, the unit price of long-term scenario is reduced by an additional 60% as indicated by [42], similar to the average case without uncertainties. For example, the upper bound price for at-launch/near-term scenario is computed as the price estimate for 5-seater multiplied by the uncertainty: \$3.884/seat-km$\times$50% = \$1.942/seat-km. The long-term price is reduced by an additional 60%, therefore \$1.942/seat-km$\times$40% = \$0.7768/seat-km.

Table 4.2: Price and Aircraft Model for Uncertainty Analysis

Scenario	Sub-scenario	Unit Price (\$/seat-km)	Aircraft Model
At-launch/Near-term	Upper bound	1.94	Joby
	Average case	4.52	AutoFlight V1500
	Lower bound	6.79	CityAirbus NextGen
Long-term	Upper bound	0.777	Joby
	Average case	1.81	AutoFlight V1500
	Lower bound	2.71	CityAirbus NextGen

Figure 4-9: Aircraft Specifications for Uncertainty Analysis [80] [11] [3]



Chapter 5

Results

This section presents the results of the scenario analysis. With the fast-forwarding trend toward UAM, the at-launch scenario results are first presented in detail to provide insights into the characteristics of potential UAM demand in the upcoming years. Finally, near-term and long-term scenario results are presented and the results of all three scenarios are compared, which enables the observation of the potential UAM demand changes over time with varying supply constraints.

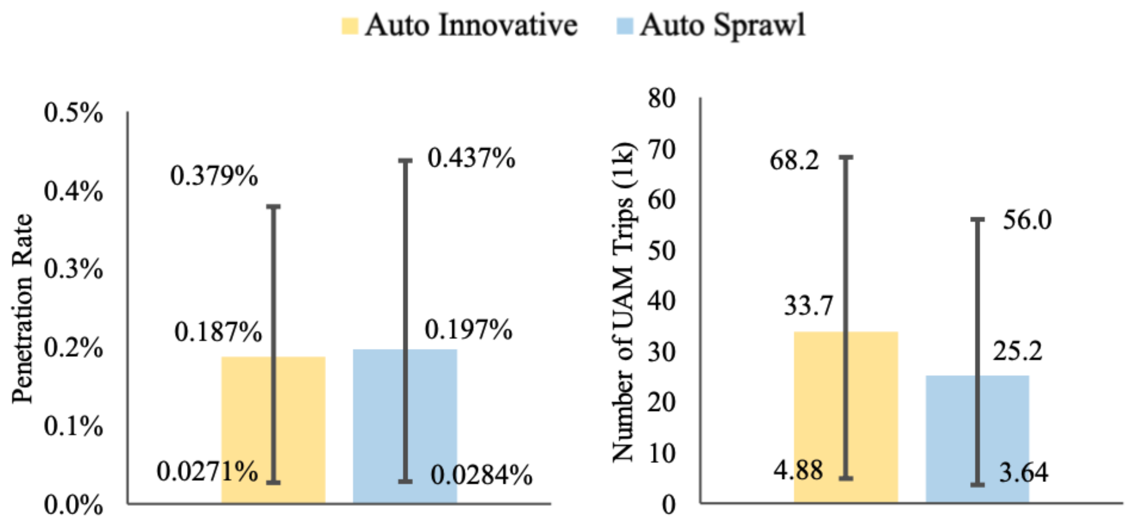
5.1 Potential UAM Demand at Launch

In this section, the potential market sizes with uncertainties are first presented in Section A. Section B and Section C present additional results of the average case without uncertainties. The number of iterations taken for the day-to-day learning process to converge is three for AS and four for AI, with an initialized total passenger waiting time of 20 minutes for all zonal pairs.

A Market Size

The market size results, including penetration rate and the number of daily UAM passenger trips, are shown in Figure 5-1, with the uncertainties. While the market penetration rates are similar, the number of UAM trips is higher in AI than AS. One reason is the larger addressable market in AI: there are in total 18.0 million trips in AI and 12.8 millions in AS. In addition, the average time saving is 59.2 minutes in AI and 53.7 minutes in AS. Thus, demand in AI is higher as UAM saves more time. Lastly, AI individuals have higher income distribution, which indicates higher VOT. The uncertainty is shown to be large in both cities, indicating that variations in price, aircraft type, and unobserved factors, e.g., public perception, play significant role in determining potential UAM demand. However, the upper bounds of penetration rate of both cities are less than 0.5%, indicating that the potential market of UAM is niche when just launched. The scale of the market size is similar to the results of existing studies that used agent-based simulations [67] [74] [63].

Figure 5-1: UAM Demand in At-Launch Scenario



B Demand Characteristics

UAM demand characteristics are investigated for at-launch scenario average case with no uncertainties. Figure 5-2 presents the UAM penetration rate by trip purpose, which shows that penetration rate among work trips is higher than non-work trips in both cities. While work trips defined in this thesis do not distinguish between regular commute and business trips, similar results have been found by [38] and [40] that UAM is most likely to be used for business trips.

Figure 5-2: UAM Penetration Rate by Trip Purpose

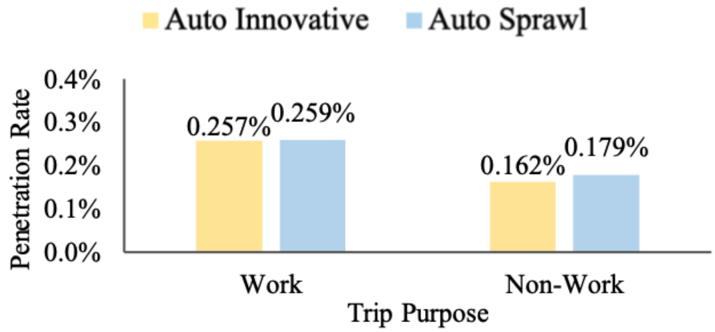
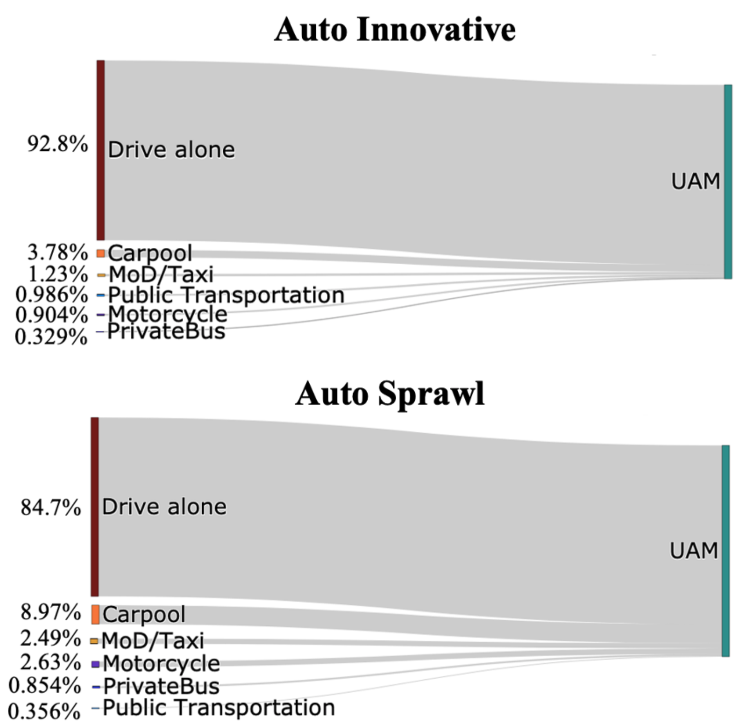


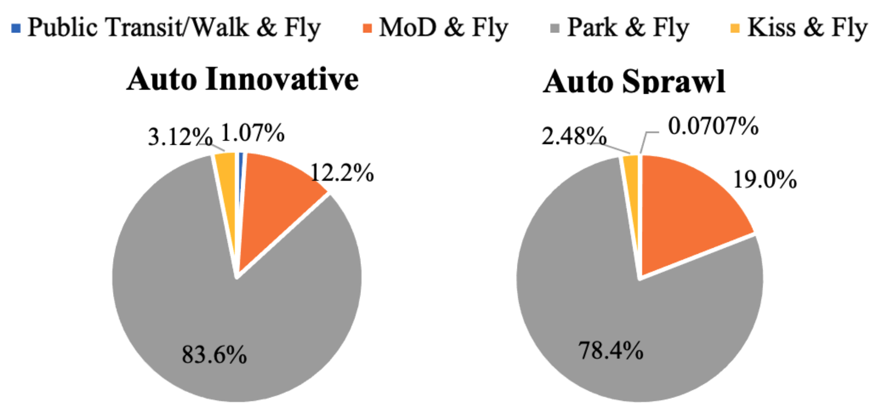
Figure 5-3 presents the modal shift in at-launch scenario, which compares the shares of the chosen non-UAM modes from which switching happened. The majority of the switchings come from drive-alone trips, but the shares are different between AI and AS: 92.8% in AI and 84.7% in AS, indicating that UAM is more appealing to individual drivers in AI than in AS. Carpool and MoD/Taxi are the other major modes where UAM demand switched from, though the shares are small: around 5% in AI and 10% in AS.

Figure 5-3: Modal Shift



The access/egress mode shares of UAM trips are shown in Figure 5-4. Most of the trips are park and fly. Thus, most individuals prefer drive-alone for UAM access/egress. As noted before, the majority of the UAM trips come from current drive-alone trips. These results suggest that UAM travelers are mainly the car-oriented individuals. Furthermore, MoD for access/egress has higher share in AS than in AI, which could be due to the lower MoD cost in AS. Therefore, drive-alone and MoD are the most preferred modes for UAM access/egress, which is supported by [92] and [42].

Figure 5-4: Access/Egress Mode Share



C Supply

For each of AM, Off-Peak (OP) and PM periods, an hour representative of the demand is selected to perform the simulation. For AM and PM, the hours selected capture the peak demand, while, for OP, the hour captures the lowest demand at midday. For both cities, the selected hours are 7:30 AM to 8:30 AM, 11 AM to 12 PM, and 4 PM to 5 PM.

Fleet size, hovering time, and total passenger waiting time results are presented in Table 5.1 for at-launch average case sub-scenario. The total passenger waiting time at equilibrium is around 14 minutes for peak hours in AI, but only around 7.5 minutes for AS. This indicates that individuals in AI are willing to accept higher waiting time than those in AS, as UAM also has higher time saving in AI. The hovering times are low for both cities in all simulation periods, but OP hovering time is lower than the two other periods due to the lower demand.

At equilibrium, the fleet size required for AI is 350, which is lower than the 600 for AS. This is due to the spatial distribution of the vertiports, and the UAM demand generated. Recall that AS has two major cities with high density of vertiports. Similar pattern of UAM demand has also been observed: it is highly concentrated around the two cities, with only a few traveling in between. Therefore, to satisfy the demand, the fleet size needs to be large enough to serve both cities separately to avoid having to rebalance between the cities. For AI, which has vertiports densely located near the sole major city at the center of the study area, since a large fleet consumes resources at vertiports and leads to congestion, the fleet size should be kept small for efficient operations. Hence, AS has a larger fleet than AI.

Table 5.1: At-Launch Scenario Average Case Simulation Results

City	**Auto Innovative**			**Auto Sprawl**		
Period	**AM**	**OP**	**PM**	**AM**	**OP**	**PM**
Fleet size	350	300	350	500	500	600
Hovering time (second)	6.84	0.656	11.7	9.90	2.40	9.83
Total passenger waiting time (minute)	13.5	5.66	14.4	7.18	6.41	7.99

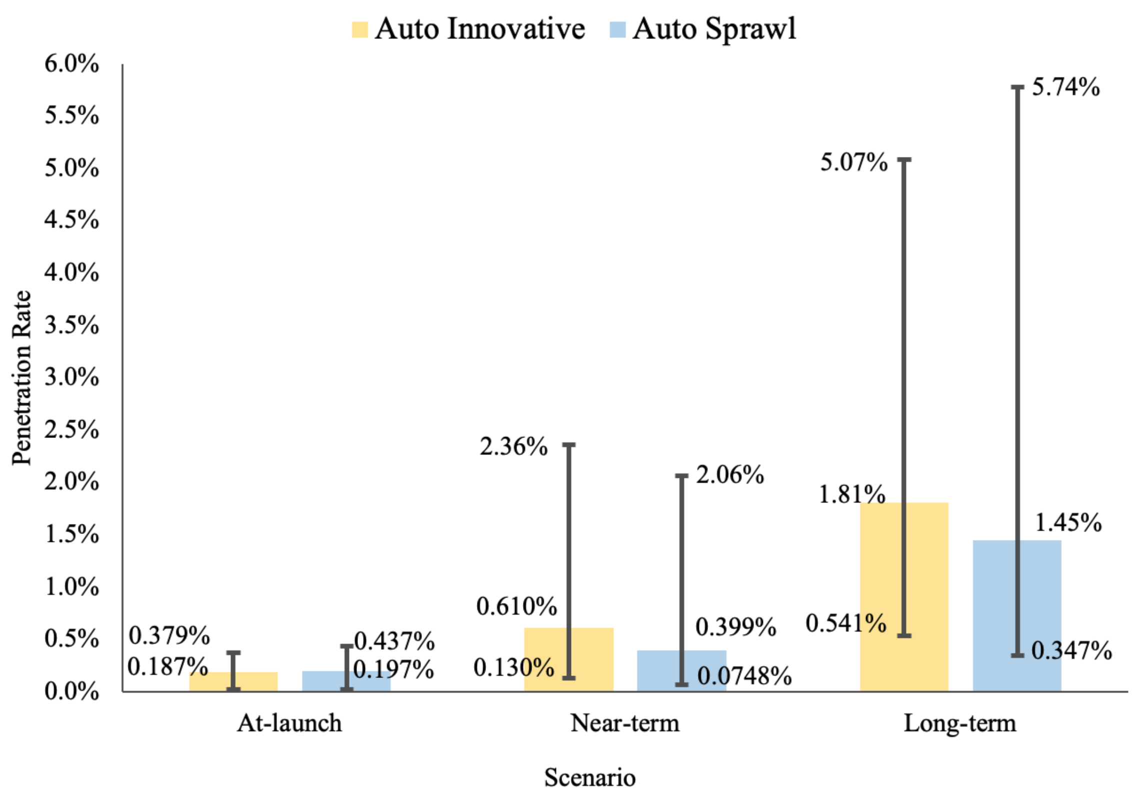
5.2 Potential UAM Demand in Near- to Long-Term

While the previous section presents the results of at-launch scenario, this section compares three scenarios varying in capacity, accessibility, and pricing. Section A compares the potential market size with uncertainties. Section B, Section C and Section D present results for the average case sub-scenarios only.

A Market Size

The penetration rates across all scenarios are shown in Figure 5-5, along with the uncertainties. While the penetration rate of AI is smaller than AS in the at-launch scenario, when supply constraints are lifted, AI has higher penetration than AS. In the near-term scenario, for AI, the penetration rate is increased by 226% (from 0.187% to 0.610%), and is further increased by 196% in long-term (from 0.610% to 1.81%). For AS, the increases are 102% and 265%. Therefore, different supply constraints affect the cities differently. The uncertainties grow when moving further down into the future. While similar in at-launch and near-term scenarios, the uncertainty of AI is smaller than AS in the long-term. One reason could be the larger long-range demand in AS than in AI, with individuals traveling between the two major cities. As long-range UAM trips are more expensive and AS has lower income, AS individuals are more sensitive to price changes in the long term when price is the major limiting factor.

Figure 5-5: Penetration Rate Across Scenarios



Define the penetration rate of long-range trips as the number of UAM trips with flight distance greater than 40 km divided by the total number of trips that would have flight distance greater than 40 km if using UAM. Penetration rate among short-range trips is defined similarly, with flight distance below 40 km. For the long-term average case sub-scenario, the penetration rates among long-range trips are respectively 4.68% and 2.35% for AI and AS. However, in the long-term upper bound sub-scenario, the rates increased to 18.5% and 19.4% for AI and AS, which are 296% and 727% increases from the average case. With a price as low as $0.777/seat-km in the long-term upper bound sub-scenario, AS is then able to capture significantly more demand. This may thus contribute to the higher uncertainty in AS in the long-term scenario.

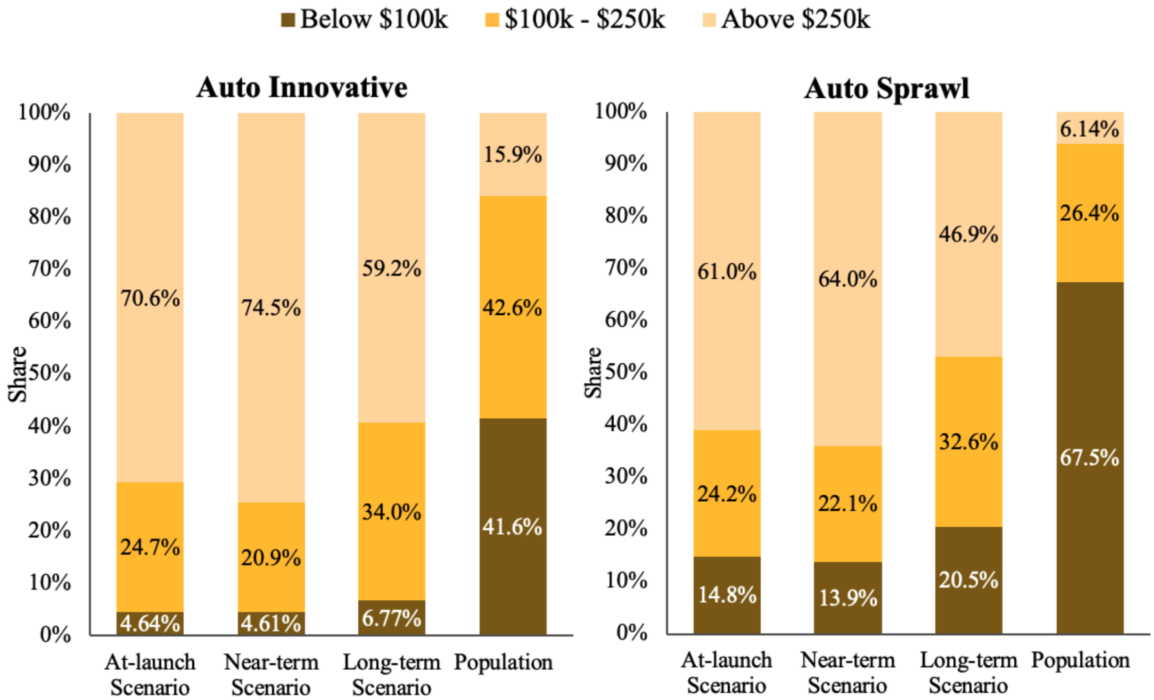
B Potential User Income Distribution

Figure 5-6 presents annual household income distribution of the potential UAM users in average case sub-scenarios, compared to the population distribution. While individuals belonging to a household with an annual income greater than $250k only constitute 15.9% and 6.14% of the total population of AI and AS, they are the majority of the UAM users and equity issue exists in all three scenarios. Similarly, it has also been found in the literature that high-income individuals are more likely to use UAM [40] [38]. Overall, UAM users in AI have a more skewed income distribution than AS. In at-launch scenario, while 70.6% of the UAM users in AI belong to the high-income class, a smaller portion of the UAM users in AS, 61.0%, belong to this class.

In near-term scenario when capacity is increased, in both cities, the shares of high-income individuals among all UAM users increase. In AI, while the share of low-income class below $100k remains unchanged, the share of middle-income class between $100k ad $250k has a nearly 4% decrease from 24.7% to 20.9%. Similarly, in AS, middle-income class is affected more than low-income class. This indicates that equity is exacerbated in near-term scenario, especially enlarging the gap between the middle- and high-income classes. Although the overall penetration rate increases, UAM is more exclusive for the high-income individuals in the near-term scenario when capacity constraint is lifted.

In the long-term scenario, however, the equity gap is decreased compared to both at-launch and near-term scenarios. From at-launch to long-term scenario, high-income class has decreases in share of respectively 11% and 14% in AI and AS. At the same time, middle-income class has 9.3% and 8.4% increases in share for AI and AS. The low-income class has 2.1% and 5.7% increases in share for AI and AS. Thus, in the long term, although equity issue still persists, it is alleviated as compared to at-launch scenario, with improved accessibility and reduced pricing.

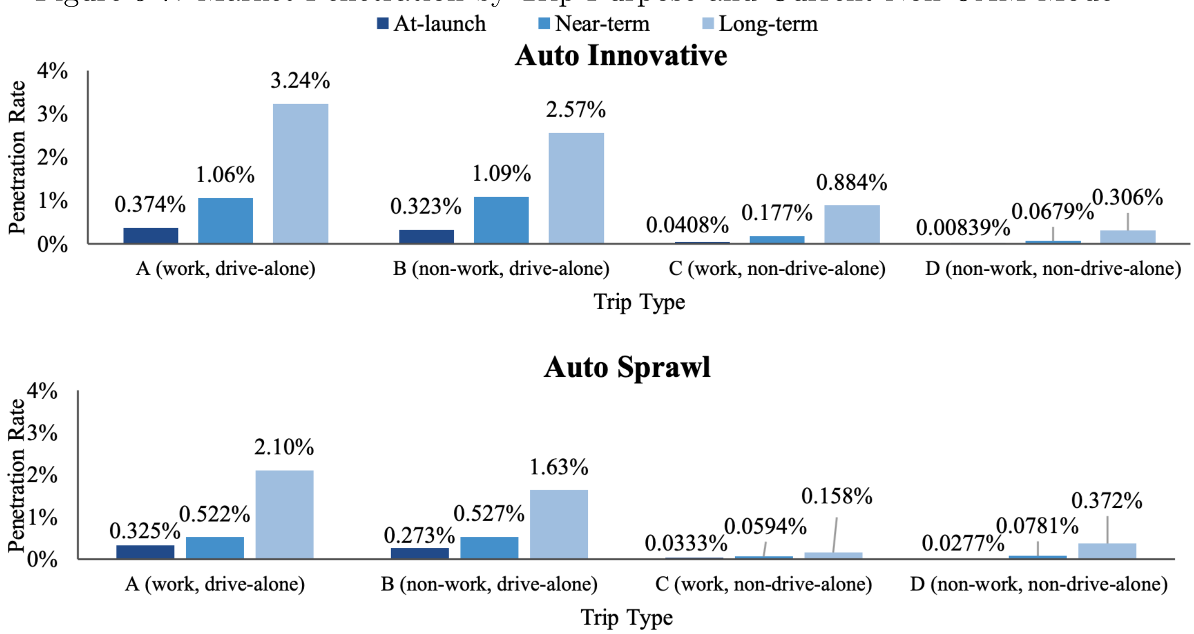
Figure 5-6: UAM Users Annual Household Income Distribution



C Market Size by Trip Type

As observed in Chapter 5.1 Section B, work and current drive-alone trips constitute the major UAM demand. Therefore, the market penetration rate changes over a combination of trip purpose and current non-UAM mode are presented in this section, with the following trip types: (A) work and drive-alone, (B) non-work and drive-alone; (C) work and non-drive-alone; (D) non-work and non-drive-alone. Figure 5-7 shows the results for the average case sub-scenarios. Overall, penetration rates increase for all types in both cities, and the increases are more significant in the long-term than in the near-term scenario. Across the scenarios, type A remains as the one with the highest penetration rate, and type B the second highest. In the long-term scenario, type C's penetration rate increases significantly in AI but not in AS. Lastly, type D sees significant increases in both cities: while nearly zero in at-launch scenario, the penetration rates of AI and AS increase to 0.306% and 0.372% in the long-term scenario respectively. This indicates that, in the long term, the UAM market attracts not only work and drive-alone trips, but others as well, opening up opportunities for various trip types.

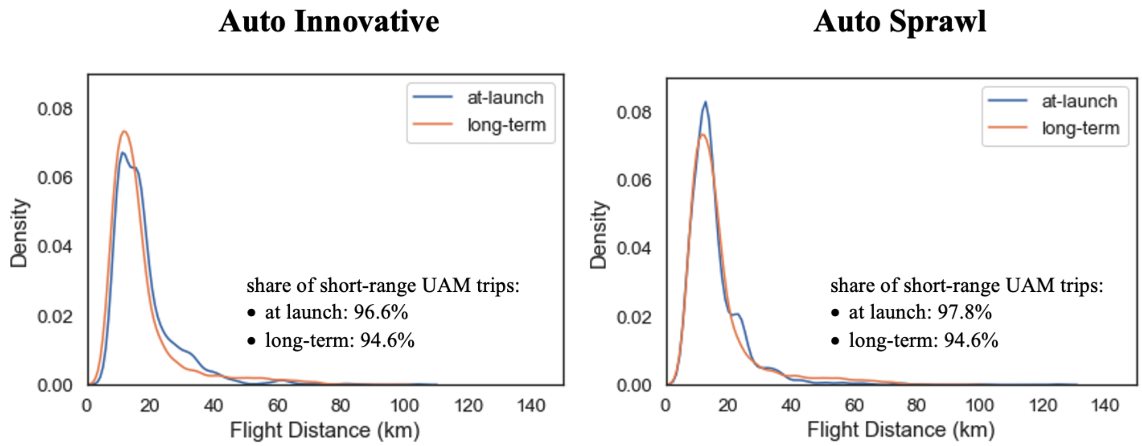
Figure 5-7: Market Penetration by Trip Purpose and Current Non-UAM Mode



D Market Size by Flight Distance

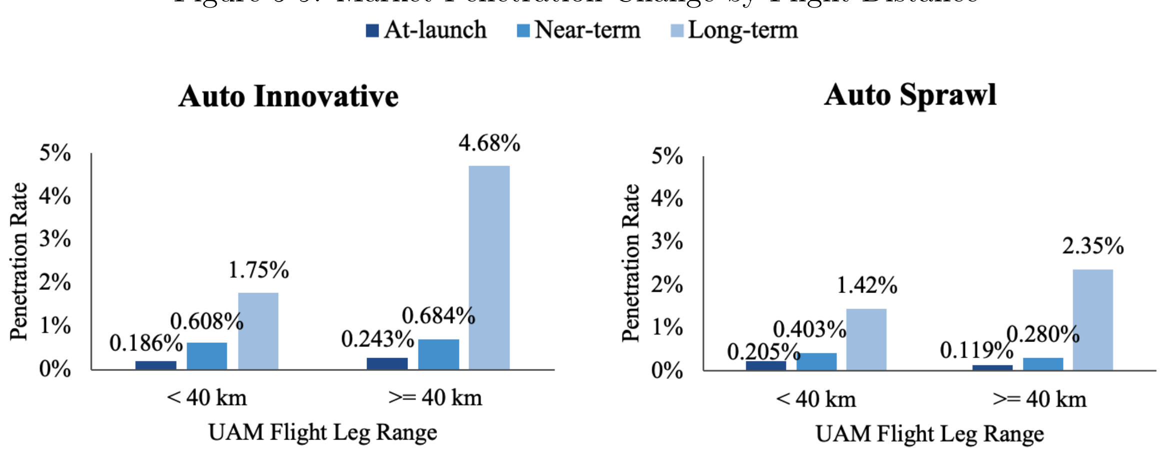
Figure 5-8 shows the UAM demand flight distance distribution in at-launch and long-term scenarios without uncertainties, presenting two extreme cases. Thus, similar to the findings of [39], the majority of the UAM trips are short-range with a flight distance below 40 km, with a share of over 90% in both cities and both scenarios. In the long-term scenario, there are less short-range UAM trips but still over 90%. This could be due to the lack of demand to travel long-distance in an urban setting and the higher cost to travel long-distance UAM trips.

Figure 5-8: UAM Flight Distance Distribution



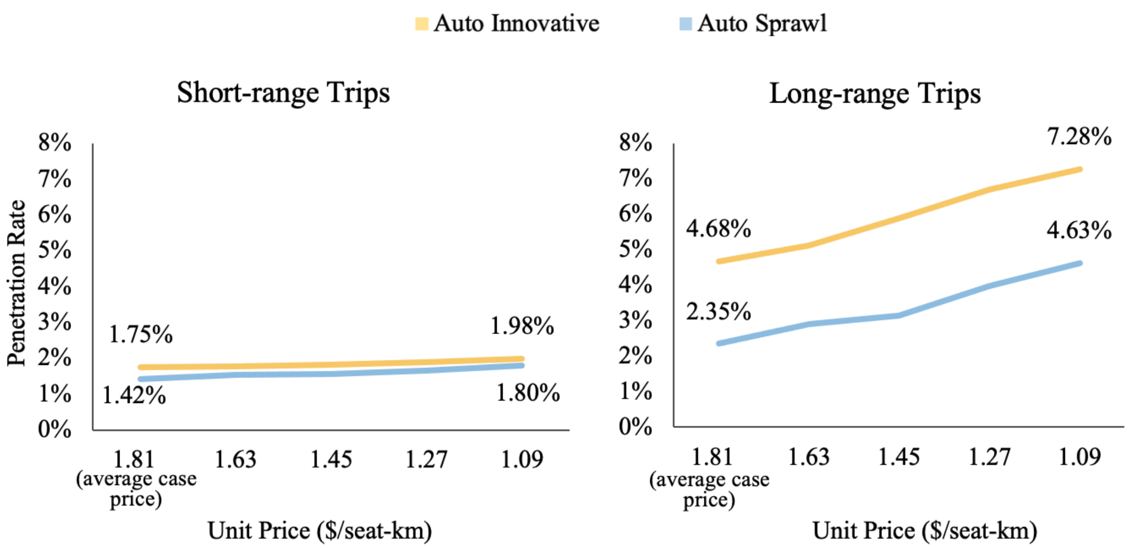
The market penetration rates across different trip distance are compared in Figure 5-9. For AI, the penetration rate of long-range trips is higher than short-range across all scenarios. The difference is the largest in the long-term scenario. On the contrary, in AS at-launch and near-term scenarios, the penetration rate of short-range trips is larger. One reason could be that long-range trips are not as affordable as short-range trips in at-launch and near-term scenarios. However, price is significantly reduced in the long-term scenario. As AS has a lower income distribution, affordability has been shown to be the limiting factor to capture the expensive long-range demand in AS.

Figure 5-9: Market Penetration Change by Flight Distance



Lastly, price sensitivity analysis has been performed for long-term scenario. The penetration rate change by flight distance is shown in Figure 5-10, with a price factor of 90%, 80%, 70% and 60%. Therefore, in the long-term scenario, the change in penetration rate among short-range trips is small. For the long-range trips, however, even though the price is low already in the average case sub-scenario with \$1.81/seat-km, the change in penetration rate is still significant as price decreases. Price is the limiting factor to capture long-range demand as a change in unit price is magnified significantly by distance and is reflected in the total price.

Figure 5-10: Long-term Scenario Price Sensitivity Analysis by Flight Distance



Chapter 6

Discussion

The analyses performed in this thesis suggest that, in the long term, the UAM market is on average around 1.5%, but with high uncertainty. The Transportation Network Companies (TNC), including Uber and Lyft, have a low share as well years after entering the market: The Metropolitan Area Planning Council (MAPC) of Boston reported a 2.41% share of ride-hailing in 2018 [41]. However, the impact on the urban transportation network is significant: e.g., Vehicles Miles Traveled (VMT) has increased, which has significant implications for congestion and pollution [31] [46]. Therefore, prior to the introduction of UAM, policymakers should be mindful of its impact on the existing transportation network, perform careful analysis and make informed decisions. This section summarizes the major findings and policy implications observed in this thesis.

UAM has been shown to be a potentially niche market that exhibits equity issues. The majority of the UAM users are high-income individuals with an annual household income above $250k, constituting around half of the UAM users in the long term. However, these individuals only constitute 6% to 16% of the total population in the two cities studied. Results indicate that increased capacity would exacerbate the issue in the near term. However, in the long-term scenario, with increased accessibility and reduced pricing, the issue could be alleviated, although still persists. Thus, regulators should be aware of this potential equity issue and design policies to remedy it: e.g., how to use UAM to complement public transit and to improve accessibility for underdeveloped areas may be investigated in future studies.

Understanding the type of trips that UAM capture is important for policymakers to properly design regulations, and for operators to tailor the marketing strategies. In this thesis, the analysis shows that UAM has a potentially high penetration rate among work and current drive-alone trips. However, in the long term, the penetration rates over other types of trips also increase, bringing new opportunities. For example, penetration rate among non-work and non-drive-alone trips increase from nearly zero in the at-launch scenario to around 0.3% in the long-term scenario. As individuals use UAM for various purposes in the long term and UAM enlarges the area that people may travel within, it could potentially bring about increases in economic activities in less urban areas (e.g., rural or underdeveloped areas). Therefore, future studies could be performed to analyze the impact of UAM on regional development and explore its potentials.

The majority of the potential UAM users are shown to be car-oriented. Most of the switching come from current drive-alone demand in both cities. While they switch to UAM, drive-alone is still the most preferred mode for access/egress to/from the vertiports. Thus, the infrastructure needs near the vertiports should be designed to support the parking demand. Improper designs could lead to increased driving time searching for parking, thus exacerbating traffic condition near the vertiports [9]. For UAM to be incorporated into the existing transportation network with minimal risks, careful analysis should be done to evaluate the impact of the UAM vertiport parking demand, and to compare the performance of different solutions: e.g., policymakers may encourage the service operator to cooperate with the TNCs to provide packaged service of UAM that includes discounted access/egress trips with MoD and thus avoid parking demand; shuttle services may also be deployed. However, further research is needed to address this issue and cost-benefit analysis may be done.

Finally, the major potential UAM demand come from short-range trips with a flight distance less than 40 km, even though, in the long term, the penetration rate among the long-range trips is higher. As the literature shows that short-range UAM trips may be less energy-efficient than long-range trips, it is critical that the operator and policymakers evaluate the environmental impact of UAM trips by distance [49]. Proper regulations could be introduced to avoid serving the energy-inefficient short-range trips: e.g., imposing taxes on emissions; providing incentives for users to use pooled UAM trips to increase occupancy.

Chapter 7

Conclusion

7.1 Conclusion

In this thesis, the potential UAM market size and demand characteristics, along with the impacts of supply on demand, have been analyzed, including the impact of capacity, accessibility, and pricing. An agent-based simulation framework has been proposed to comprehensively model UAM demand, supply, and their interactions at fine spatial and temporal levels. The approach has been implemented in the state-of-the-art mobility simulation platform, SimMobility, and includes the following considerations:

1. A demand-centric vertiport placement with realistic vertiport capacity generation;

2. Explicit UAM service operations that include rebalancing, charging, and transition activities at vertiports;

3. A behaviorally sound representation of underlying decision-making process that captures switching behavior with the introduction of UAM.

Based on the analyses of two prototype cities, it is found that the potential market of UAM is niche for high-income individuals and has high penetration rate among work and drive-alone trips, and hence are likely to raise equity concerns. On average, the penetration rate is less than 0.2% at launch and ranges between 1.45% to 1.81% in the long term for the two cities that were studied. The majority of the potential UAM users are found to be car-oriented, who still prefer drive-alone for access/egress to/from the vertiports. While long-range trips greater than 40 km flight distance have a higher penetration rate in the long term, short-range trips still constitute the majority of the potential UAM demand. It has been found that supply constraints on capacity, accessibility, and pricing have significant impacts on demand, which are found to be city-specific. Overall, in the long term, supply constraints may be lifted, which could increase the potential demand, help alleviate the underlying equity issue, and bring new opportunities for all types of trips. However, equity issue still exists in the long term, which policymakers should be mindful of.

7.2 Future Work

There are several limitations and future research may be performed to address the questions unanswered.

Firstly, the induced demand may be included in the demand model. As UAM increases the transport supply, new trips may be generated, as with the case of High Speed Rail (HSR), with which traveling is more frequent due to the change in supply, e.g, faster traveling speed [21]. However, in this thesis, the focus is diverted demand from other modes.

Second, in this thesis, work trips do not distinguish between regular commute and business trips. However, some studies have highlighted the significance of business trips, even though the comparisons between commute and business trips have not been studied yet to the best of the author's knowledge [38] [40]. Therefore, detailed analysis of the UAM work trips by commute or business purposes may be performed in the future.

Thirdly, the UAM service controller developed could be further improved. First, efficient operation algorithms based on optimization models may be incorporated with the service controller, which will enable the analysis of impact of service operation efficiency on UAM demand. Second, an energy model may be added to investigate the environmental impact of UAM. In addition, while price is static in all scenarios studied by this thesis, the suppliers may also adjust the service price in each iteration of day-to-day learning to optimize their profits. Such dynamics may be modeled in future study as well.

Lastly, while vertiport capacity is taken into consideration, it has been implicitly assumed that there will be space available at the vertiports for the aircrafts waiting for available gates after landing. However, this assumption may not be true in the real-world setting. Aircrafts may need to reroute to a nearby hub to wait for available space at vertiports and for missions to be assigned. Therefore, future research could be conducted to address this limitation.

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