Chair of Transportation Systems Engineering
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Flow- and Pricing-based Urban Air Mobility Demand Estimation for Local and Non-Local Travellers

An Île-de-France Case Study

A thesis presented in part fulfilment of the requirements of the Degree of Master of Science in Transportation Systems at the Department of Civil, Geo and Environmental Engineering, Technical University of Munich.

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Submitted on München, 22.05.2022

Abstract

Urban Air Mobility (UAM) is a quite new topic which is expected to offer a new mode of transport to bypass the growing traffic congestion in the urban area via flying cars. Many companies which are developing electrical aerial vehicles are vying to come first to the market. Before introducing UAM as a new mode of transport and integrating it to the existing transportation network, it is a prerequisite to find the behaviour of its potential customers. The aim of this study is to estimate the potential UAM demand captured from different groups of travellers under different UAM operating factors and fare schemes, taken into account the local and non-local travellers in Île-de-France, France. For this purpose, a transportation model has been developed in which UAM has been integrated as new mode of transport. The results indicate that the majority portion of UAM demand is captured from airport passengers, following by tourists. However, a negligible number of residents are willing to use UAM, even in the cheapest fare schemes, although the total number of trips for this group are much higher than airport passengers and tourists. The results have also revealed that UAM potential customers are more sensitive to distance-based fare in comparison with base fare. The findings provide meaningful insights for stakeholders to know the potential customers and most influential factors on their behaviour in short-term and medium-term implementation of UAM.

Acknowledgements

This study has been carried out as the final Master's Thesis of Master's Program in Transportation Systems at the Technical University of Munich and in cooperation with Volocopter GmbH, a German aircraft manufacturer based in Bruchsal, Germany. The completion of this thesis would not have been possible without the support and help I have got during last months.

I am extremely grateful to Ralf Frisch, my external supervisor from Volocopter, for his invaluable assistance and insights to the complementation of this thesis. This work would not have been possible without Ralf who has facilitated this journey at many bottlenecks.

I greatly appreciate my university supervisor Dr. Raoul Rothfeld for his guidance in all steps of my work. I am very thankful for his availability, encouragement, and constructive feedback. His instructions have been sometimes equivalent to a shortcut shortening the path.

Finally, I owe my utmost gratitude to my family, especially to my dear wife and our daughter, who have stood by me during this journey.

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List of Abbreviations

_75	Département of Paris
_77	Département in which Disney-Land is located
_78	Département in which Versailles is located
AA	Attraction-Attraction
AH	Attraction-Hotel
ASC	Alternative Specific Constant
BF	Business French tourists
BI	Business International tourists
H_	High class Accommodation
HA	Hotel-Attraction
L_	Low Class Accommodation
MATSim	Multi-Agent Transport Simulation
PF	Personal French tourists
PI	Personal International tourists
PuT	Public Transport
RP	Revealed Preference
SP	Stated Preference
UAM	Urban Air Mobility
UAMaaS	Urban Air Mobility as a Service
UAT	Urban Air Taxi
UnP	Unpaid accommodation

1. Introduction

Growing mobility demand because of rapid urbanisation results in increase of traffic congestion, which is the main issue in transportation, particularly in metropolitan areas around the world. Although the cities are not able to increase the road capacities due to land consumption, it has been already found that roads' capacities expansion is a contributing cause for traffic growth (Tennøy, Tønnesen, & Gundersen, 2019). Urban Air Mobility (UAM) is a quite new topic introducing a new mode of transport for the urban area via flying vehicles. However, bypassing the traffic congestion through using the third-dimension dates to 1960s in U.S. (Lynn, 2016). Considering the recent rapid technological developments in the transportation industry, too many companies around the world have already started working on flying demonstrators, including well-known companies such as Airbus and Boeing as well as a large number of start-ups like Volocopter and Ehang (Straubinger, et al., 2020). While racing to come first to the market, these companies are trying to develop electrical aerial vehicles which are energized with renewable resources and offered services in an affordable price for all the groups of passengers.

1.1. Research Motivation

It is completely obvious that UAM is going to be a new mode of transport for urban mobility, and this emerging mode of transport will sooner or later penetrate the market. Needless to say, it is a prerequisite to find the behavior of potential customers before introducing new products to the market. Therefore, the mode choice behavior of prospective users of UAM needs to be assessed. Based on this assessment, UAM could be integrated into to the existing network so as to attract passengers as much as possible. Employment of a transportation model could facilitate the above-mentioned processes.

In recent years, many studies have been done to predict demand for this novel mode of transport. A considerable number of the studies have used well-known agent-based model to model the transportation network including UAM, (Balac, Rothfeld, & Hörl, 2019; Rothfeld (1), Fu, Bala´c, & Antoniou, 2021; Rothfeld (2), 2021; Rothfeld, Balac, Ploetner, & Antoniou, 2018). In addition, in the most of studies that have estimated the potential UAM demand, UAM has been modeled as an on-demand service. Being an on-demand mode is in contrast with the time-saving feature of UAM, which is the most claiming advantage of UAM. Fleet-size and infrastructure constraints make the on-demand UAM an unreliable service as there is no guarantee that there is an air-taxi vehicle at arrival time of passenger at vertiport so that he/she has to wait to get the first coming vehicle. Last but not least, concerning the potential costumers, to the best of the author's knowledge, there is no study considered all possible travelers in a given network, including residents, airport passengers, and tourists.

Moreover, the manufacturers are hardly trying to find the cities with the highest potential in where they could persuade the corresponding authorities while competing to win the market. Considering the population, airport passengers, and tourists, Île-de-France is an ideal location to explore UAM services, and many companies, like Volocopter, Airbus, and Joby Aviation, have already targeted this region (ADP, GROUPE ADP, 2021).

1.2. Objectives and Research Problems

The main objective of this thesis is to estimate UAM potential demand in a pricing- and flow-based approach for local travelers, i.e., residents, and non-local travelers, i.e., tourists and airport-passenger, in Île-de-France region, France. To be more specific, the impact of different UAM operating variables as well as different fare combinations on the UAM flow will be assessed. This assessment could help the stakeholder to know users with the highest potential, the impact of each variable on different target groups, and the best fare combination for each group of customers.

Therefore, this thesis aims at answering the following questions:

1. How does each target group react to different fare schemes in different scenarios?
2. How does the UAM demand change under different UAM operating variables?
3. What are the main target groups for the selected fare schemes?
4. What is the best fare scheme for each group of customers?

1.3. Thesis Structure

This thesis is structured as follows. Chapter 2 presents a literature review including definition of UAM, potential users of UAM, review of the models and use cases employed UAM, and factors influencing UAM usage. After that in chapter 3, the implemented UAM network in the current study will be detailed. Chapter 4 presents data collection and preparations processes, compromising introduction to the study area and its attributes, components of selected modes of transport, and data collection and preparation for each model. Later in Chapter 5, the model development is elaborated, from raw data to importable data for a transportation model. Chapter 6 provides the results of implemented scenarios for all target groups. Chapter 7 discusses the main findings of this thesis. Chapter 8, finally, gives the conclusion, limitations, and further steps of this project.

2. Literature Review

This chapter goes through the literature and previous research in four main sections. First, the concept of urban air mobility is defined. In the next section, an in-depth review on different target groups which have been considered as the potential users of UAM service is provided. Section 2.3. presents a thorough review of the models and use cases that have applied and employed for UAM. As the aim of the current study is to assess the UAM demand under different variables, especially fare' variables, a comprehensive review is presented in section 2.4 in which different examined and influential factors from literature are explained.

2.1. Urban Air Mobility

Urban Air Mobility (UAM) is a transportation system that envisions a safe, sustainable, affordable, and accessible air transportation system for passenger mobility, goods delivery, and emergency services within or traversing metropolitan areas (Cohen, Shaheen, & Farrar, 2021). In the current study, the UAM refers to passenger mobility only. UAM is aiming to reduce the travel time by using the third dimension and bypassing traffic congestion. For this purpose, a multitude of companies have already started developing electric vertical take-off and landing aircrafts (eVTOLs) (Straubinger, et al., 2020).

2.2. Target Groups

Focusing on trips purposes, Straubinger et al. (Straubinger, Michelmann, & Biehle, 2021) present five segments as potential customers for UAM, which are inner-city commuter/citizens, outside commuters/suburban dwellers, airport-passengers, tourists, and companies. In another study, Goyal et al. s (Goyal, et al., 2018) identified 36 potential demand markets across 16 market categories, like air commute, first response, and event. The authors later introduced three focus markets on which they have done market analysis, which are airport shuttle, air taxi, and air ambulance. Results of a state preference questionnaire out of the mentioned report (Goyal, et al., 2018) shows that respondents have been more receptive to using UAM for travel to the airport or long-distance recreational trips than for commuting.

Too many studies have been done to assess the potential demand and affective factors for integration of UAM, considering different costumer segments. Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have examined the local travellers, and airport passengers within the Greater Munich Area. In some similar studies the authors have assessed the implementation of UAM for local travellers, which have been residents daily trips, and airport passengers (Ploetner, et al., 2020; Balac, Rothfeld, & Hörl, 2019; Goyal, Reiche, Fernando, & Cohen, 2021). Some authors have only taken into consideration the daily movements of local travellers, deriving from well-known household travel survey (Wu & Zhang, 2021; Rimjha (2), Hotle, Trani, & Hinze, 2021; Bulusu, Onat, Sengupta, Yedavalli, & Macfarlane, 2021; Boddupalli, 2019). However, a few works have considered some segmentation that are more relevant as being potential customers of UAM. For instance, Haan et al. (Haana, et al., 2021) have questioned high-income commuters in 40 most populous cities in the U.S., and Daskilewicz et al. (Daskilewicz, German, Warren, Garrow, & Boddupalli, 2018) have filtered all high-income commuting trips longer than 30 minutes as potential trips for UAM services. Moreover, some studies have considered UAM as being a mode for airport access (Rimjha (1), Hotle, Trani, Hinze, & Smith, 2021; Roy, et al., 2020; Rath & Chow, 2019).

Regarding tourists, Jialing et al. (Jialing, Jun, Xinjun, & Honggang, 2012) have found that travel time, number of transfers, fare, and comfortableness are the four major factors to affect mode choice behaviour of tourists in the study area. Moreover, another work states that higher travel time and travel costs have been acceptable when tourists selected a complex trip chain with tour activities (Qi, Zhu, Guo, Lu, & Chen, 2020). Le-Klähn et al. (Le-Klähn, Roosen, Gerike, & Hall, 2015) have examined the tourists' mode choice behavior in Munich and found that overnight, returning, and international visitors are more likely to travel beyond the city, e.g., longer trips, than day trippers. Also, their results show that PuT is the dominant mode for tourists staying within the city, while other modes are used for traveling beyond the city.

Almost no previous work has been found in which tourists has been assessed as potential costumer for UAM service, although Rothfeld et al. have taken into consideration the main tourists' attractions to locate vertiports in Sioux Falls (Rothfeld, Balac, Ploetner, & Antoniou, 2018).

The longer-term growth of e-commerce, work-from-home/telework, and potential shifts to suburban/exurban lifestyles could also change the type of UAM uses cases envisioned (Cohen, Shaheen, & Farrar, 2021). Straubinger et al. (Straubinger, et al., 2020) have defined three operational concepts in which every concept is assumed to have a certain customer group:

- <u>UAM platinum</u> mainly targets high-income people and business travellers,
- <u>Urban Air Taxi (UAT)</u> offers cheaper prices and by that attract more potential passengers,

- UAM as a service (UAMaaS): in the long-term, it is likely that UAM will be used by different passenger groups.

Figure 1 depicts how different scenarios target different user groups and how the number of potential users increase over time. Similarly, Rath and Chow (Rath & Chow, 2019) have defined three scenarios of short-term, mid-term and long-term contributing to different air taxi prices, which short-term has the highest price.

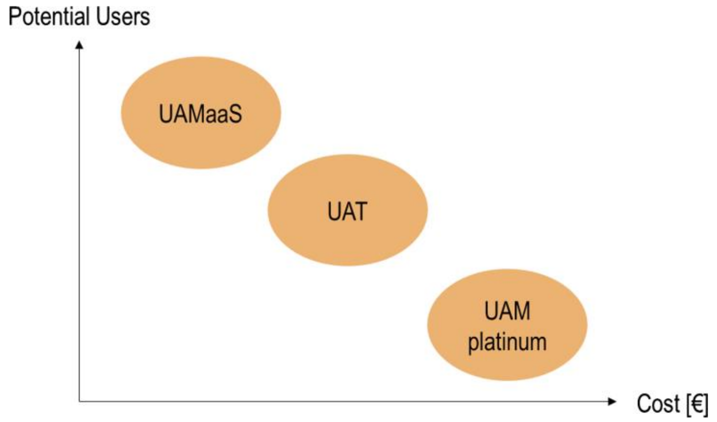

Figure 1 Categorization of operational concepts for UAM (Straubinger, et al., 2020).

2.3. Models

UAM is a new topic, therefore only a few studies have been done regarding its implementation as a mode of transport. Many of works which have integrated UAM as mode of transport into the transportation network have used agent-based models, MATSim (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021; Fu (1), Straubinger, & Schaumeier, 2020; Rothfeld, Balac, Ploetner, & Antoniou, 2018; Balac, Rothfeld, & Hörl, 2019; Ploetner, et al., 2020). Roy et al. (Roy, et al., 2020) have generated trips requests for passengers travelling from/to Hartsfield-Jackson Atlanta International Airport and used a utility-based choice model to simulate the expected mode choice behaviour of individuals. As well, Ilahi et al. (Ilahia, F.Belgiawanb, Balaca, & Axhausena, 2019) have estimated a discrete choice model using pooled SP and RP data sets to find the mode choice behaviour of respondents and how many of them will choose UAM in the Greater Jakarta. In similar studies, the data out of a stated preference surveys done in Munich has been used for developing multinomial and ordered logit mode choice models in which the participants have chosen UAM among different alternatives (Fu (2), 2018; Al Haddad (1), Chaniotakis, Straubingerc, Plötnerc, & Antonioua, 2020). Some other works have also used SP data to model mode choice behaviour in which UAM is one of the alternatives (Haana, et al., 2021). Rath and Chow (Rath & Chow, 2019) have developed a binary model with which airport's passengers have two options of air-taxi and ground-taxi as the modes of transport. Wu and Zhang (Wu & Zhang, 2021) have filtered the trips with more than 10 miles of driving distance and 30 min of travel time, assuming that shorter trips would be less appealing to use UAM. In a similar study, passengers have two options of car via road and take a multimodal trip, which UAM is a part of, to travel from origin to destination. In this model the commuter chooses UAM if the time saving is at least 25% or 50% of the road travel time (Bulusu, Onat, Sengupta, Yedavalli, & Macfarlane, 2021). Peksa and Bogenberger have used PTV Visum traffic simulation software to estimate UAM demand for Munich (Peksa & Bogenberger, 2020).

Most of the mentioned studies have considered UAM as an on-demand service, but Peska and Bogenberger have assumed that UAM vehicles in a headway-based manner (Peksa & Bogenberger, 2020). Taking into account UAM as a mode of transport, it has been found from the literature that UAM have been modelled in two different ways. First, air taxi as a single mode of transport that offers service from vertiport to vertiport (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021; Arellano III, 2020; Rothfeld, Balac, Ploetner, & Antoniou, 2018). Secondly, air-taxi is a part of a multimodal mode in which the first and/or last leg is feeding by a feeder mode (Wu & Zhang, 2021; Bulusu, Onat, Sengupta, Yedavalli, & Macfarlane, 2021; Rath & Chow, 2019).

2.4. Parameters Affecting UAM usage

Straubinger et al. (Straubinger, et al., 2020) have listed the most relevant factors for UAM, among them the travel time, travel cost, access/waiting time, value of time, and safety have been labelled with higher importance. Table 1 shows these factors, their relevance, and their possible response.

Fu (Fu (2), 2018) has conducted a preliminary study to explore preferences for transportation modes in an UAM Environment, and her results indicate that travel time, travel cost, and safety could be determinants. The results of the mentioned study also suggest that income level, age, and trip purposes could be also influential. In another study which the main objective has been to identify the factors affecting the use and adoption of UAM, factors like time savings, costs of automation, and service reliability have been found strongly influential (Al Haddad (2), 2018).

Also, Arellano III (Arellano III, 2020) has developed a procedure for allocating UAM stations by a multi-criteria decision analysis framework considering the most influential factors in UAM station placement. The procedure aims to maximise UAM for all demand points by determining demand per number of stations and travel time comparison with typical ground transportation. Table 2 shows the factors and their weights.

Relevance	Identified factor	Possible response
High	Travel time	High travel speed, not affected by congestion on the ground, on-demand service, point-to-point
High	Costs	Adaption of pricing schemes, create a good value for money
High	Access time/waiting time	Efficient connection to existing transport modes, efficient fleet management, on-demand service
High	Value of time	Maximize options for efficient use of travel time
High	Safety	High safety standards
Medium	Comfort	Comfortable vehicle interior
Medium	Flexibility	On-demand service, all routes served
Medium	Automation	Fully autonomous
Medium	Willingness to share	Single rides vs. pooled rides
Medium	Trip purpose	Identify relevant target groups
Medium	Trip distance	Identify relevant target groups

Table 1 Most relevant demand drivers of UAM, their relevance and possible responses to these (Straubinger, et al., 2020).

Factor	Average Weight
Population Density	5.3%
Median Income	12.7%
Office Rent Price	10.9%
Points of Interest	14.1%
Major Transport Node	14.7%
Average Total Transport Cost	12.3%
Job Density	8.5%
Number of Extreme Commuters	7.3%
Potential Supply	6.9%
Existing Noise	7.4%

Table 2 Factors Influencing UAM Ground Infrastructure Placement (Arellano III, 2020)

Raoul et al. (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021) have considered cruise speed, processing time, and number of UAM stations as the variables affecting UAM demand. Number of stations have been 4, 8, 24, 76, and 130, in which flights are possible between each pair of stations. Flight speeds and processing times have been varied between 60-300 km/hr and 0-30 minutes, respectively. It has been found that processing time and number of stations heavily influence the potential share of UAM. This study indicates that although higher stations substantially increased service coverage, it did not significantly reduce median travel times.

Rimjha et al. (Rimjha (2), Hotle, Trani, & Hinze, 2021) have been examined two variables influencing UAM demand, the number of vertiports and UAM cost per passenger which have been varying between 50-400 and 1-3 $/mile, respectively. The results of this study indicate that sufficient UAM demand for commuting trips can only be reached at optimistically low UAM offer fares. Also, it is stated that the UAM demand for commuting trips in some routes within the study area is heavily one-directional.

Balac et al. (Balac, Rothfeld, & Hörl, 2019) have taken into consideration different variables affecting UAM demand, such as cruise speed between 60-240 km/her, processing time between 0-12 min, base far UAM between 3-60 CHF, and variable fare UAM between 0.6-4.2 CHF/km. The authors have indicated that experiments with variable fare exceeding 1.8 CHF/km UAM service could attract very few customers, and with these pricing structures service is only attractive for the very-income segment of customers. It is stated that comparing the results of the mentioned study to an earlier work the estimated demand is drastically lower when process time, access/egress trips, and infrastructure placement are included in the decision process. Based on this study, doubling the base fare has a smaller negative influence on the demand than doubling variable costs. Moreover, it is stated that processing time and cruise speed have a non-marginal effect on the total number of UAM trips, for instance an increase in cruising speed from 60 km/h to 120 km/h has a stronger effect on the number of trips than an increase from 120 km/h to 240 km/h.

Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have done an sensitivity analysis to UAM demand by varying fleet-size, network size, UAM cruise speed, processing time, base fare, distance-based fare, which are between 10-1000 vehicles/stations, 24-130 stations, 50-350 km/hr, 0-20 minutes, 0-10 €, and 1-10 €/km, respectively. The results show that changing the cruise speed from 50 km/hr to 350 km/hr, which is 7 times higher, has just increased the UAM trips around 20%. In addition, increasing base fare from 0 to 10 € has reduced the UAM trips around 15%, comparing to changing distance-based fare from 1 € to 10 € which has reduced the UAM trips 75%. This low level of sensitivity to base fare is, most probably, due to the very low defined cost for this attribute. UAM modal share ranges from 0.03% to 1.29%, which even in the best scenario the UAM share is not sufficient to reduce the congestion. The authors have also indicated that 48-56% UAM trips are up to 10 km.

Zu and Zhang (Wu & Zhang, 2021) have stated that personal vehicle is the primary choice for vertiport access, following by bus transit. It has also been revealed that in the same number of vertiports, UAM adoption is extremely sensitive to air trip cost, which varies between 10-30 USD for base cost and 1-2 USD/mile for distance-based cost. Another influential factor stated by this study is transfer time in vertiport from/to other modes to/from UAM mode, varying from 2 to 10 minutes.

Peksa and Bogenberger (Peksa & Bogenberger, 2020) have considered comfort and fare as two influential factors regarding UAM usages. The comfort has been model as a coefficient for in-vehicle time component, varying from 0.8 to 1.2. The authors have found that comfort does not have a significant impact on the UAM performance when compared to the fare.

3. Urban Air Mobility

This chapter describes the methodology of how the UAM is modeled for this study. First, it is explained how the UAM network is created. Then, different operating components of UAM for the current study is described.

3.1. Urban Air Mobility Network

UAM network for the current study is inspired by two earlier studies done for Île-de-France region. In those studies, there have been six scenarios with 2, 4, 8, 24,76, and 130 stations in which there is a route between each pair of stations (Rothfeld (2), 2021; Rothfeld (1), Fu, Bala´c, & Antoniou, 2021). The focus of the mentioned studies has been on residents of Île-de-France, not non-local, and, therefore, most of stations have been not relevant for tourists and airport passengers. Inspired by 24 stations scenario of the mentioned studies and taken into account the locations with higher potential for non-local travelers, 18 stations have been located within the study area, Figure 2. Regarding the relevant routes for this study, a subset of possible lines between stations in four scenarios have been created, which includes 7, 18, 37, and 59 lines. Considering both direction between stations, there 18, 36, 74, and 118 routes for scenario 1-4.

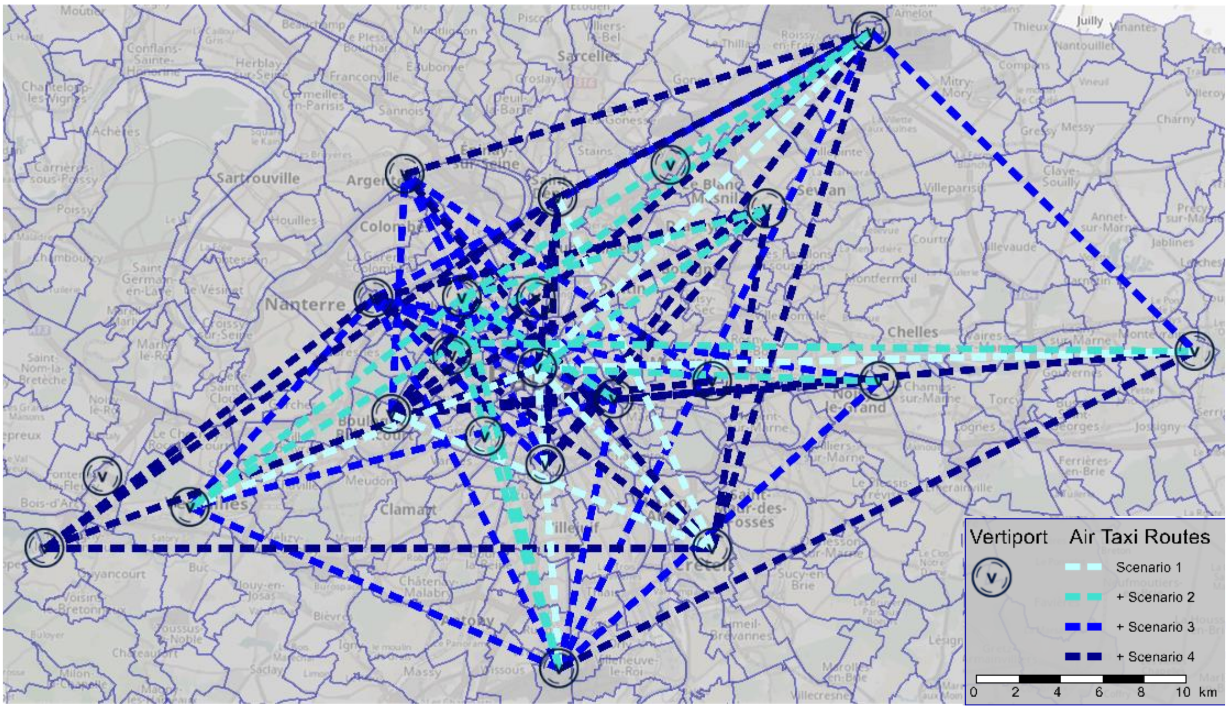

Figure 2 Network UAM stations and routes in Île-de-France.

3.2. Air-Taxi Operation

3.2.1. Vehicle

Volocity, Figure 3, has been considered for this study as the air-taxi vehicle, which is a two-seat air-taxi; Maximum flight range and maximum airspeed equal to 35 km and 110 km/hr, respectively (Volocopter, 2019).

Figure 3 Volocity (Volocopter, 2019).

3.2.2. Multimodal Mode

Similar to some earlier studies (Wu & Zhang, 2021; Bulusu, Onat, Sengupta, Yedavalli, & Macfarlane, 2021; Rath & Chow, 2019) air taxi is modeled as a part of a multimodal mode. In this project, it is assumed that the operator, Volocopter GmbH, is offering a multimodal mode of transport whose first/last leg could be served by a ground-taxi, and air-taxi is the mandatory mode. Passengers are supposed to use walking mode to access or egress from vertiport if there is a vertiport in the origin/destination zone or in a zone somewhere close to the origin/destination zone. Otherwise, the passenger needs to use taxi mode as feeder.

3.2.3. Timetable

Unlike many studies in the field of UAM, one of the particular features of the current study is the implementation of timetable-based air-taxi services. Peksa and Bogenberger (Peksa & Bogenberger, 2020) have also modeled UAM services in a headway-based manner. To this purpose, an operating duration of 16 hours from 6:00AM to 10:00PM has been considered, in which different headway could be implemented.

3.2.4. Fare

As stated in the most of earlier studies conducted to find factors influencing UAM demand, fare is one of the most determinative factors in the use of UAM. Two attributes of base fare and km-based fare have been considered in this thesis. Therefore, different values could be assigned to these variables to see the impact of fare in the current work.

3.2.5. Processing Time

Processing time is the sum of all non-flying time components that the air-taxi passengers must spend during their trips from entrance of origin vertiport to exit of destination vertiport. Some of the components of processing time are check-in duration, possible waiting after check-in, time between boarding and take-off, and time between landing and alighting. As one of the main benefits of UAM is its timesaving feature (Al Haddad (2), 2018), this time-related attribute would have an influential impact on the attitude of passengers toward UAM. This attribute has been also considered as one of the variables for the model.

If there is a transfer between different air-taxi routes, the processing time for the second flight onwards has been assumed to be half of the first flight.

3.2.6. Speed

Although speed is not considered as a factor influencing UAM demand significantly, it is a factor determining the travel time. Therefore, cruise speed is taken into consideration as one of the variables impacting UAM demand for the current work. In this study, an average speed for a direct route has been considered to represent the speed during cruising, take-off, and landing.

3.2.7. Access Time

This attribute has been found as a determining factor for the use of UAM in earlier studies (Balac, Rothfeld, & Hörl, 2019; Straubinger, et al., 2020). Thus, access time to vertiport is another taken variable for the model. As mentioned earlier, air-taxi has been defined as a part of a multimodal mode. Thus, passenger could access to or egress from vertiport in two ways, depending on the existence of vertiport in origin/destination zone.

Walking: First, access/egress via walking mode for the zones that has a vertiport or there is a direct connector to the vertiport in a neighbor zone.

Feeder: If the origin/destination zone of the trip does not have a vertiport or a connector to a vertiport, ground-taxi plays the role of the feeder.

3.2.8. In-Vehicle Time

As it will be come later, the coefficient of in-vehicle time for all modes of transport is 1. During the first years of operation, being in a flying vehicle has, most probably, a fun aspect, particularly for tourists. Considering this aspect, the impact of this attribute on the UAM demand could be assessed trying different coefficients for in-vehicle time, like an earlier study in which coefficient of in-vehicle time has been considered as a representative factor for comfortableness (Peksa & Bogenberger, 2020).

3.2.9. Skim Matrices

PuT skim matrices for Volocity and Feeder: The skim matrices of the modes forming multimodal mode, i.e. Volocity and Feeder, have been calculated in order to have the skim matrices for multimodal mode. Thus, using "Calculate PuT skim matrix" procedure in PTV VISUM the following skim matrices for Volocity as a PuT mode have been calculated, which are In-Vehicle Time, Number of Transfer, and Ride distance. For taxi mode, the relevant matrices, which will be explained later, have been employed.

Multimodal Mode skim matrices: Table 3 shows the coefficients and matrices which have been employed for calculation of skim matrices for Multimodal mode.

Mode		Travel Time Reliability	Travel Time (minute)	Cost (€)
Feeder (first and last leg)	Ground-Taxi	[90th–50th Percentiles Travel Time]	[Travel Time by Car] + 2 minutes (transfer time)	Max (7.3, (2.6 + 1.38* [Distance]+ 0.71 *[Travel Time]))
	OR			
	Walking	-	[Access/egress time to/from vertiport] (for each leg)	-
Volocity		-	[In-Vehicle Time] + [Processing time] * (1 + 0.5 * ([Number of transfers]))	[Base fare] *([Number of Transfer]+1) + [km-base fare] * [Ride Distance]
Multimodal mode		Sum of above cells	Sum of above cells	Sum of above cells

Table 3 Skim matrices calculation for Multimodal Mode.

4. Data Collection and Preparation

This chapter contains three main parts. In the first part, the study area is introduced, following by describing its attributes and traffic data. Later, the features and components of selected modes of transport, excluding UAM, for the current study are presented. Finally, the procedures regarding data collection and preparation for each model, which are airport model, tourism model, and residential model, are explained.

4.1. PTV VISUM

PTV VISUM software, which is a transport planning software, provided by PTV GROUPE (GROUPE, 2022) has been employed to simulate the network for this thesis.

4.2. Study Area

The study area in this thesis is Île-de-France region, which is the most populated region in France and home to more than 12 million inhabitants (Insee, 2021). In addition, this region is one of the most visited cities in the world where has been the destination to more than 20 million international tourists in 2019, out of 50 million tourists visited this region (CRT, 2019). Moreover, the second busiest airport in the Europe, Charles de Gaulle International Airport, is located in this region. Based on GROUPE ADP (ADP, 2020) around 76 million passengers used this airport in 2019.

Considering all the mentioned number in the previous paragraph, Île-de-France seems to be an area with a high potential for exploring UAM, which several studies have been done in this regard to assess vertiports location and UAM demand (Rothfeld (2), 2021; Rothfeld (1), Fu, Bala´c, & Antoniou, 2021).

4.3. Zoning

The main source for zoning of the study area has been IRIS zoning systems (IRIS, 2019), but some modifications has been applied on it. First, due to limitation of existing software license, it has been needed to reduce the number of zones. Therefore, the zones located far away from the central zones and at the edge of the region have been removed. It needs to be mentioned that those zones have been also out of our interested quarters within the study area and out of reach considering the maximum range of Volocity. Secondly, a different zoning level other than IRIS zoning system have been implemented for the district of Paris because of the availability of data for this district.

4.3.1. Zones' Attributes

<u>Hotels:</u> IRIS dataset (Insee, 2021) includes hotels' information, such as hotels' classification and capacities across Île-de-France. Hotels' information has been imported into the model as points of interest (POIs). Using intersecting feature in PTV VISUM, this information has been converted into zones' attributes. To be more specific, several hotels with different classifications and capacity located in one zone have been summed up, based on their classifications and capacities.

<u>Commerce, Restaurants, and Schools/Universities:</u> These attributes have been used as factors showing the attractivity of different zones for different demand models and demand strata. The location of commercial areas, Restaurants, School/Universities are included in IRIS dataset (Insee, 2021) as POIs. This attribute has been also intersected with zones so as the number of commercial areas per zone have been available.

<u>Workplaces:</u> Number of jobs per zone has been used as an attribute to represent number of workplaces per zone. IRIS dataset (Insee, 2021) also includes the number of jobs per zone, but the zoning level for the inner ring, Paris 75, is different than this study's zoning system. To convert the information to the current zoning level, a regression analysis for zones out of inner ring has been done, in which number of jobs has been the independent variable. For the regression model, commerce, population, etc. have been considered as the dependant variables. Therefore, knowing the total number of jobs for inner zones, the regression model has been employed to distribute the number of jobs to the zones located in inner ring.

<u>Number of Visitors (Touristic Trips):</u> This attribute has been used as the attractivity factor for touristic trips. Two groups of attractions have been considered for this attribute, sum of them taken as the attractivity factor.

- <u>Major Attractions:</u> Ministère de la Culture (Ministère de la Culture, 2019) and Comité Régional du Tourisme Paris (CRT, 2019) provide the number of visitors per year for the most visited places, 70 attractions, in Île-de-France, like museums and palaces. Therefore, the number of tourists visiting these attractions is computable for a given day, dividing by 365. The locations of these attractions have been imported into the model and intersected with zones. As a result, an attribute called number of visitors per zone has been created which could be used as the attractivity factor for touristic trips.

- <u>Minor Attraction:</u> Moreover, IRIS dataset (Insee, 2021) includes an attribute showing the locations of all attractions in Île-de-France, which has been converted into a zone attribute.

Knowing the tourists’ trip rate, the total number of daily visits for Île-de-France has been calculated. On the other hand, the number of visits to major attractions is already known. The difference between these two numbers has been allocated to the zones weighted by the number of minor attractions that each zone has.

4.4. Network and Traffic Data

A network including the operational speeds for the period of 2019.09.01-2019.10.31 provided by TomTom (TomTom, 2019) has been implemented. TomTom data includes different percentile speeds and sample size for each individual links along the day for all links located in Île-de-France. Three attributes have been used, which are median speed, the 10th percentile speed, and sample size. Using the 10th percentile speed, the 90th percentile travel time for later implementation have been calculated.

4.5. Skim Matrices

Median Travel Time: The 50th percentile speed has been used to calculate travel time matrices between zones. Two median travel time matrices have been calculated: Morning peak hour, 8:00 AM - 9:00 AM, and the average of median travel time from 6:00 AM to 10:00 PM weighted by sample size. These matrices have been created for later applications.

90th percentile travel time: The 10th percentile speed has been used to calculate 90th travel time matrices between zones. Like median travel time, two matrices have been calculated for morning peak hour and average from 6:00AM to 10:00PM.

Travel time radiality: Travel time reliability is a fundamental factor in travel behaviour. It represents the temporal uncertainty experienced by travellers in their movement between any two nodes in a network (Carrion & Levinson, 2012). This factor has been considered for those modes that uses the ground network in this study, expect for PuT. As stated by Carrion and Levinson(Carrion & Levinson, 2012):

$$RR = \frac{VOR}{\mathrm{VOT}} \quad (1)$$

Where VOR is the value of reliability, VOT is the value of travel time, and RR is the reliability ratio. Carrion and Levinson have grouped different transformation ratios with which the importance of travel time reliability could be taken into consideration, Table 4. In the current study 90th–50th Percentiles has been selected and the correspond travel time skim matrices has been calculated, which means the difference between the median and 90th travel time. This matrix has been employed for mode choice calculation.

Measure	Ratio
Standard deviation	1.000
90th–50th Percentiles	0.780
80–50th Percentiles	1.188
75th–25 Percentiles	0.741

Table 4 Transformation ratios for a normal distribution (Carrion & Levinson, 2012).

Distance: Distance matrices include the ground distance between all zones which has been used to calculate cost matrices for taxi and car modes. The matrices' values could highly depend on the time of the day, as there are different speed and travel time along the day, and, consequently, the distance corresponding to the shortest travel time has been selected for each pair of zones.

4.6. Modes of Transport

4.6.1. Public Transport

For this mode of transport skim matrices had been already calculated by other colleague in earlier step of the project, and these matrices have been employed for the model: Skim matrices for fare and travel time between all the zones. Indeed, the perceived journey time has been used for PuT inspired by French experience stated in by Meuniera and Quinet (Meuniera & Quinet, 2015). Table 5 depicts the employed coefficients for different travel time components. It has been assumed that all the demand strata in three different models have the same attitude regarding the perceived travel time by PuT.

Time component	Coefficient
In-Vehicle time	1
Transfer waiting time	1.5
Access/Egress time	1.5
Walking time before and after transport	2
Number of transfers	5 min

Table 5 Travel time components

4.6.2. Car, Car-Dropped-off, and Taxi

The travel time and distance matrices have been used to compute travel time and costs matrices for modes of Car, Car-Drop-off, and Taxi. Table 6 shows the coefficients used for these calculations. It should be mentioned that the values stated in Table 6 are relevant for Île-de-France region.

Matrix	Mode	model	Function
Travel Time (Minutes)	Taxi	All models	1* [Travel Time Matrices] + 7.5 minutes (to find a taxi)
	Car Drop-off	All models	1* [Travel Time Matrices] + 3 minutes (to get/park vehicle at home)
	Car	Airport	1* [Travel Time Matrices] + 3 minutes (to get/park vehicle at home) + 10 minutes (to park/get car at airport)
		Touristic	1* [Travel Time Matrices] + 5 minutes (to get/park vehicle at hotel) + 15 minutes (to park/get at destination)
		Residential	1* [Travel Time Matrices] + 5 minutes (to get/park vehicle at home) + 10 minutes (to park/get car at destination)
Cost (€)	Taxi	All models	Max (7.3, (2.6 + 1.38* [Distance]+ 0.71 *[Travel Time]))
	Car Drop-off	All models	0.41 * [Distance] * 2 (distance for two direction)
	Car	Airport	0.41 * [Distance] + 0.5 * 75 (half of parking price for 3 days at airport, 25 €/day)
		Touristic & Residential	0.41 * [Distance] + 0.5 * 12 (half of parking price for 3 hours, 4 €/hour)

Table 6 Skim matrices' functions for Car, Car-Dropped-off, and Taxi modes for Île-de-France

4.7. Airport Passengers (First Model)

4.7.1. Data Collected

Orly and CDG airports have been taken into consideration for airport model, and monthly traffic of these two airports for October 2019 released by GROUPE ADP has been used (ADP, 2020). As well, different information regarding the origin/destination of passengers within different districts of Île-de-France and the modal split for all the passengers have been given by GROUPE ADP during the exchanging meetings.

4.7.2. Demand Strata

The demand strata related to the segmentation of different group of passengers have been defined according to the available data. The data given by GROUPE ADP has been dividable into different segmentations based on being resident/non-residents and business/non-business. Moreover, two segmentations for business passenger travelled in business/first-class have been created, which is representative for the high-income business passengers. Table 7 shows different demand strata for airport model.

4.7.3. Trips Generation and Distribution

Using the dataset provided by Paris Tourist's Authority (CRT, 2019), it has been known how many of business and non-business tourists are arriving/departing by airplane, which tourists equal to non-residents. Taking into consideration these proportions, the airport passengers' origin/destination, and some zone's attributes, trips from/to airports have been distributed to different zones for different demand strata. Table 7 shows the distributing factors which have been employed for each demand stratum.

For instance, considering business residents demand strata, the provided data by GROUPE ADP (ADP, 2020) includes the number of business passengers have gone to Département of Paris (75). From another dataset it is known that how many of business non-residents travelers stayed in this Département. Therefore, taken into consideration two above values, number of business residents gone to Département of Paris have been calculated. This Département includes 96 zones, which each zone has the attributes of the capacity of different hotel classification and number of workplaces. Finally, the business resident travelers have been distributed based on hotel capacities and number of workplaces among zones with the weights of 80% and 20%, respectively.

Demand Stratum	**Hotel Capacity**	**Workplaces**	**Population**
Business/ Non-Residents Business/ Non-Residents/ Hi-Income	80%	20%	0%
Business/ Residents Business/ Residents/ Hi-Income	0%	20%	80%
Non-Business/ Non-Residents	100%	0%	0%
Non-Business/ Residents	0%	0%	100%

Table 7 Airport model demand strata and used their distributing attributes

4.7.4. Modal Split

Segmentation	**Car**	**Drop-off**	**Taxi**	**PuT**
Non-Residents – To airports	-	22.6 %	41.3 %	36.1 %
Residents – To airports	12.0 %	19.9 %	36.4%	31.7 %
Non-Residents – From airports	-	18.2 %	33.4 %	48.4 %
Residents – From airports	9.9 %	16.4 %	30.1%	43.6 %

Table 8 Airport's passenger modal split.

The given information for airports includes the modal split of the whole passengers, not for different demand strata. There are two modal splits for trips to airports and trips from airports. The only differentiation is between residents and non-residents, in which Car has not been considered for non-residents. Table 8 shows the modal split for different demand strata of airport's passengers. It needs to be mentioned that some modes has been aggregated.

4.7.5. Value of Time

Regarding the level of income, with which the value of travel time could be calculated, no information/data has been provided for Île-de-France airports' passengers. Therefore, some researches have been done in this regard. As stated in (VTPI, 2020) the value of travel time could be a percentage of income. In addition, the value of travel time highly depends on the trip purpose (VTPI, 2020; Wardman, K.Chintakayala, & Jong, 2016; Wang & Hensher, 2015). For instance, the value of travel time for business trips could be 80%-120% of household hourly income, and for leisure passengers travelling by airplane 60%-90% of household hourly income. To calculate the value of travel time for air passengers, the values of travel time provided by Meuniera and Quinet (Meuniera & Quinet, 2015) for French travelers have been employed for resident's travelers, and for non-residents travelers a proxy with the similar airports like Heathrow airport (CAA, 2019) has been done. For instance, for Heathrow it is stated that 3.2% and 2.9% of business passengers have the income level of "230,000-350,000£" and ">35,000£", respectively. It has been already known that the proportion of first/business class passengers, high-income business travelers, is around 4% in Île-de-France airports. A proxy has been done between these two sets of information and assumed that first/business class passengers have an annual income of 300,000 €, consequently 147 €/hr. Table 9 depicts the selected value of travel time for different demand strata.

Demand Stratum	**VoT (€)**
Business/ Non-Residents	50
Business/ Non-Residents/ Hi-Income	147
Business/ Residents	50
Business/ Residents/ Hi-Income	147
Non-Business/ Non-Residents	37.5
Non-Business/ Residents	25

Table 9 Value of travel time for airport passengers.

4.8. Tourists (Second Model)

4.8.1. Data Collected

For touristic model, a very rich dataset has been provided by Île-de-France tourist authority (CRT, 2019) which includes a wide variety of information; An intersected segmentation of different parameters such as nationality, trip's purpose, type and location of accommodation, daily activities, expenses, and chosen modes of transport.

4.8.2. Demand Strata

The demand strata for touristic models have been created according to the available data to consider the most determinative factors regarding mode choice behavior. The travelers have been segmented based on their nationality, trip's purpose, and type of accommodation. Type of accommodation is a factor to take into account the income level. Table 10 shows the demand strata for touristic model. It needs to be mentioned that the business-related trips of tourists have not been considered.

It is known from the dataset (CRT, 2019) what proportion of each demand stratum has been stayed in which department within Île-de-France. As depicted in Table 10, three different types of accommodation have been considered; H refers to 4- and 5-stars hotel, L refers to 1-, 2-, and 3- stars hotel as well as non-classified hotels, and UnP means those type of accommodation which the tourists have not paid for. Tourists visiting family or staying with friends are two examples of UnP accommodation. These groups of tourists have shown quite different behavior, e.g., different daily activities and chosen modes of transport.

Segmentation				Explanations
BF_H	BI_H	PF_H	PI_H	Trip Purpose: • B: Business • P: Personal Nationality: • F: French • I: International Type of Accommodation: • H: High-class hotels • L: Low- and middle-class hotels • UnP: Unpaid accommodation _77: the department in which DisneyLand is located _78: the department in which Versailles is located
BF_L	BI_L	PF_L	PI_L	
BF_UnP	BI_UnP	PF_UnP	PI_UnP	
BF_H_77	BI_H_77	PF_H_77	PI_H_77	
BF_L_77	BI_L_77	PF_L_77	PI_L_77	
BF_UnP_77	BI_UnP_77	PF_UnP_77	PI_UnP_77	
BF_H_78	BI_H_78	PF_H_78	PI_H_78	
BF_L_78	BI_L_78	PF_L_78	PI_L_78	
BF_UnP_78	BI_UnP_78	PF_UnP_78	PI_UnP_78	

Table 10 Touristic model demand strata and used their distributing attributes

Disneyland, Versailles are among the most attractive places in Île-de-France located out of city Centre Paris, Department of Seine-et-Marne (77) and Yvelines (78), respectively. As stated by Jin and Xu (Jin & Xu, 2018), tourists are overly sensitive toward trip's distance and choose the attractions around the accommodation place. In addition, looking through the activities of different groups of tourists in these two departments, it has been seen that their activities are different from tourists in other departments. For instance, the possibility of visiting Disneyland for a tourist staying in Department of Seine-et-Marne is much higher than a tourist staying in Department of Paris, and vice versa. Therefore, two different sets of demand strata for the departments in which these two places are located have been created.

4.8.3. Trips Generation and Distribution

As a prerequisite, the tourists have had to be allocated to zones. It is known what portion of each demand stratum have stayed in each department. Therefore, having the capacities of different hotel classifications and population for each zone, the tourists have been allocated to each zone weighted by hotel capacity or population. For instance, it is stated that how many of non-French business tourists stayed in 4- and 5- stars hotel in Department of Paris, the tourists have been distributed among different zones of this department weighted by the capacities of 4- and 5- stars hotels. This allocation which is a zone-based attribute, has been used to generate trips from zones.

There is another attribute which is responsible for attracting trips from other zones. The attribute of daily visitors of zone, and the number of restaurants has been used as the attractivity attributes for zones, but the daily visitors attribute is the major attribute.

Three types of trips have been considered for touristic model, home-attraction, attraction-attraction, and attraction-home, which home is accommodation in where the tourists have stayed. These three types cover all tourists' movement patterns provided by some earlier studies (Mckercher & Lau, 2008; Hofer, Haberl, & Fellendorf, 2016). Moreover, number of visited places per day for each demand stratum has been calculated using the information from dataset. For example, a tourist who has visited 2.5 attractions have had 1 home-attraction trip, 1 attraction-hotel trip, and 1.5 attraction-attraction trips per day. The derived trip rates for different demand strata are comparable with the rate in other studies. For instance, Hofer et al. (Hofer, Haberl, & Fellendorf, 2016) have modeled the tourists' trips in the province of Salzburg, which is a small region in comparison with Île-de-France. In the mentioned study in which the author has only considered the visit of cultural sites, trip rates vary from 2.1 to 3.4 per day.

4.8.4. Modal Split

One of the information provided in the dataset (CRT, 2019) is the main modes of transport that have been used by different demand strata. Taking into account some assumptions and modifications, the modal split for each demand stratum has been calculated. First, different types of public transport have been aggregated. Secondly, it is assumed that those tourists have used taxi and car would have not used other modes of transport, and the rest distributed among PuT and walk. Thirdly, Metro has been considered as the representative of PuT. Finally, Bike has not been considered as a mode of transport. Table 11 shows the modal split for all demand strata, and Table 12 shows an example of modal split calculation for demand stratum PI_H_78.

Segmentation	Taxi	Car	Walk	PuT	Segmentation	Taxi	Car	Walk	PuT
BF_H	44.9%	20.9%	10.6%	23.5%	PF_H	31.6%	36.6%	12.2%	16.2%
BF_L	23.9%	22.1%	16.9%	35.9%	PF_L	16.6%	36.0%	18.7%	28.7%
BF_UnP	17.9%	26.9%	17.8%	37.5%	PF_UnP	12.6%	47.0%	14.9%	25.5%
BF_H_77	27.6%	48.9%	11.4%	12.0%	PF_H_77	8.6%	56.9%	23.2%	11.2%
BF_L_77	11.0%	54.4%	12.1%	16.4%	PF_L_77	6.1%	59.6%	19.6%	14.7%
BF_UnP_77	6.4%	57.1%	14.2%	22.3%	PF_UnP_77	2.8%	79.0%	8.6%	9.6%
BF_H_78	23.9%	39.6%	15.9%	20.6%	PF_H_78	13.3%	63.1%	10.1%	13.5%
BF_L_78	14.2%	53.0%	9.7%	18.3%	PF_L_78	8.5%	66.8%	11.2%	13.5%
BF_UnP_78	7.3%	48.4%	14.1%	30.2%	PF_UnP_78	4.7%	71.8%	10.8%	12.8%
BI_H	55.0%	14.4%	9.6%	21.0%	PI_H	40.2%	10.8%	19.0%	29.5%
BI_L	33.2%	13.2%	15.5%	34.9%	PI_L	23.2%	9.5%	23.2%	42.3%
BI_UnP	27.5%	21.2%	15.1%	36.2%	PI_UnP	20.3%	27.9%	16.6%	35.1%
BI_H_77	44.0%	21.9%	13.4%	20.7%	PI_H_77	20.0%	22.7%	30.5%	26.8%
BI_L_77	23.7%	19.7%	11.4%	22.6%	PI_L_77	12.5%	32.5%	27.8%	27.2%
BI_UnP_77	23.7%	19.7%	11.4%	22.6%	PI_UnP_77	7.7%	67.0%	9.4%	16.0%
BI_H_78	55.2%	26.1%	5.3%	13.4%	PI_H_78	42.8%	47.0%	4.6%	5.6%
BI_L_78	37.5%	23.5%	4.1%	10.4%	PI_L_78	11.5%	49.0%	14.6%	14.7%
BI_UnP_78	20.9%	21.7%	19.0%	38.4%	PI_UnP_78	10.2%	62.8%	9.2%	17.8%

Table 11 Tourists' modal split.

<table>
<tr><td>Taxi</td><td>Car</td><td>Metro,Tramway, RER</td><td>Bus</td><td>Train</td><td>Walk</td><td>Bike</td><td rowspan="2">→</td></tr>
<tr><td>42.8%</td><td>47.0%</td><td>37.3%</td><td>13.7%</td><td>19.1%</td><td>30.9%</td><td>0.7%</td></tr>
<tr><td>Taxi</td><td>Car</td><td>Rest = 100 % - (Car + Tax)</td><td rowspan="2">→</td><td>Taxi</td><td>Car</td><td>$\mathbf{PuT} = \frac{\mathbf{Metro}}{\boldsymbol{Metro + Walk}} * \boldsymbol{Rest}$</td><td>$\mathbf{Walk} = \frac{\mathbf{Walk}}{\boldsymbol{Metro + Walk}} * \boldsymbol{Rest}$</td></tr>
<tr><td>42.8%</td><td>47.0%</td><td>10.2%</td><td>42.8%</td><td>47.0%</td><td>5.6%</td><td>4.6%</td></tr>
</table>

Table 12 Modes' share calculation for PI_H_78.

4.8.5. Value of Travel Time

The value of travel time for tourists is not a well-researched topic. Therefore, there has not been any document to refer. However, with the help of the tourists' dataset (CRT, 2019), the value of travel time for different tourists' demand strata have been calculated using some proxies. The dataset includes the relevant transport expenses during the stay, consequently daily transport expenses. Hence, the relative relationship of transportation expenses of all demand strata has been calculated, that means how one demand stratum is willing to pay less or more in comparison with another demand stratum. For instance, high-income business international tourists are willing to pay 4 times more than low-income personal French tourists for daily transportation. To calculate the value of travel time, high-income business international tourists has been considered as the reference. It has been assumed that travelers arrived at Île-de-France by airplane belongs to high-income segmentation. Therefore, the value of travel time for high-income business international tourists have been calculated by the employment of income information of Heathrow airport (CAA, 2019). Multiplying the relative ratios of all demand strata by the value of travel time of BI_H, this attribute has been calculated for all demand strata, Table 13.

Demand Stratum	VoT (€)
BF_H	46
BF_L	31
BF_UnP	22
BI_H	63
BI_L	35
BI_UnP	22
PF_H	20
PF_L	14
PF_UnP	11
PI_H	27
PI_L	21
PI_UnP	16

Table 13 Value of travel time for tourists.

4.9. Residents (Third Model)

4.9.1. Data Collected

For this model, the results of an agent-based scenario for Île-de-France developed by Hörl and Balac (Hörl (1) & Balac, 2021; Hörl (2) & Balac, 2021) has been employed. The authors have indeed proposed an open-source and extendable pipeline for travel demand synthesis for Île-de-France, from publicly accessible raw data to a final agent-based transport simulation. To have travel demand for residents, the approaches described in (Hörl (2) & Balac, 2021) and (Hörl (3), 2021) have been followed, so as the synthetic population of Île-de-France has been created. After having run the relevant codes, the results have looked like the well-known Household Travel Survey, which contains the information about the demographic, socioeconomic, and trip-making characteristics of individuals and households.

4.9.2. Demand Strata

Segmentation for residential model has been created based on two attributes, level of income and trip's purpose. It has been seen that the level of income has impact on the mode choice behavior. Looking at income distribution of surveyed household, they have been segmented into two groups of low-income and high-income groups. As well, the chosen mode is highly affected by the trip purpose. The trips are the pair of different purposes at origin and destination. Home, Education, Work, Leisure, Shop, and other have been stated as origin/destination, and in the current study Leisure, Shop and Other have been aggregated as Other for simplification. Furthermore, during the calibration of the results, some pairs of origin-destination which have not had enough data have been omitted, for example Work-Education, Education-Work and Other-Education. Table 14 shows the demand strata for residential model.

4.9.3. Trips Generation and Distribution

Derived results from the agent-based model are point to point trips for a sample size. However, zone-based trips for the whole population within the study area have been needed to be employed for the current study. Therefore, some calculations have been done on the raw data, derived from agent-base model, to make them importable into the zone-based model.

First, the raw data has been imported into PTV VISUM, in which the zones have already existed. Then, the origin and destination of trips have been intersected with the zones, it means that all origin/destination' points located within the zone A have been assigned to zone A and this zone is origin/destination of the relevant trips. After this step, all trips are between zones instead of points.

Checking the origin-destination (OD) pairs, it has been found that there are not any trips between some pairs of zones, particularly some zones that are neighbors. To fill this gap, a capability of PTV VISUM has been employed, which is aggregation and disaggregation of zones and main zones. For this purpose, zones have been aggregated into main zones, which are made up of several zones themselves. Figure 4 depicts the main zones of the study area. Using the aggregation procedure in PTV VISUM, which means trips of several zones have been integrated in one main zone, trips have been assigned to main zones instead of zones. Afterwards, having weighted the origin and destination based on certain attributes, the trips have been disaggregated from main zones to zones, via matrix disaggregation procedure within PTV VISUM. For instance, considering WBO_H which is the matrix for trips done by high-income group from work to other, the origins of trips in main zone have been distributed weighted by number of jobs in each zone, and destinations weighted by number of commerce in zones, as stated in PTV VISUM manual (GROUP, 2022):

Demand Stratum	Purpose		Income Level	Disaggregation Attribute	
	Origin	Destination		Origin	Destination
HBW_L	Home	Work	Low	Population	Workplaces
HBW_H	Home	Work	High	Population	Workplaces
HBEDU_L	Home	Education	Low	Population	Schools
HBEDU_H	Home	Education	High	Population	Schools
HBO_L	Home	Other	Low	Population	Commerce
HBO_H	Home	Other	High	Population	Commerce
EDUBH_L	Education	Home	Low	Schools	Population
EDUBH_H	Education	Home	High	Schools	Population
EDUBO_L	Education	Other	Low	Schools	Commerce
EDUBO_H	Education	Other	High	Schools	Commerce
WBH_L	Work	Home	Low	Workplaces	Population
WBH_H	Work	Home	High	Workplaces	Population
WBO_L	Work	Other	Low	Workplaces	Commerce
WBO_H	Work	Other	High	Workplaces	Commerce
OBH_L	Other	Home	Low	Commerce	Population
OBH_H	Other	Home	High	Commerce	Population
OBW_L	Other	Home	Low	Commerce	Workplaces
OBW_H	Other	Home	High	Commerce	Workplaces
OBO_L	Other	Other	Low	Commerce	Commerce
OBO_H	Other	Other	High	Commerce	Commerce

Table 14 Residents demand strata, and disaggregation attributes.

$$b_{ij} = \frac{w_{ij}^{(1)} w_{ij}^{(2)}}{\sum_{k\in I}\sum_{l\in J} w_{kl}^{(1)} w_{kl}^{(2)}} \cdot a_{ij}$$

(2)

Where $w_{ij}^{(1)}$ and $w_{ij}^{(2)}$ are the weighting attributes for origin and destination, a_{ij} is the main zone matrix, and b_{ij} is the disaggregated zone matrix.

Finally, to have the trips for the whole population, the expansion factor of each zone has been multiplied by the number of trips for each demand stratum. This factor equals to the ratio of population of zone per the number of surveyed residents in the same zone. Consequently, the trips matrices of the whole population in different demand strata have been available for further steps.

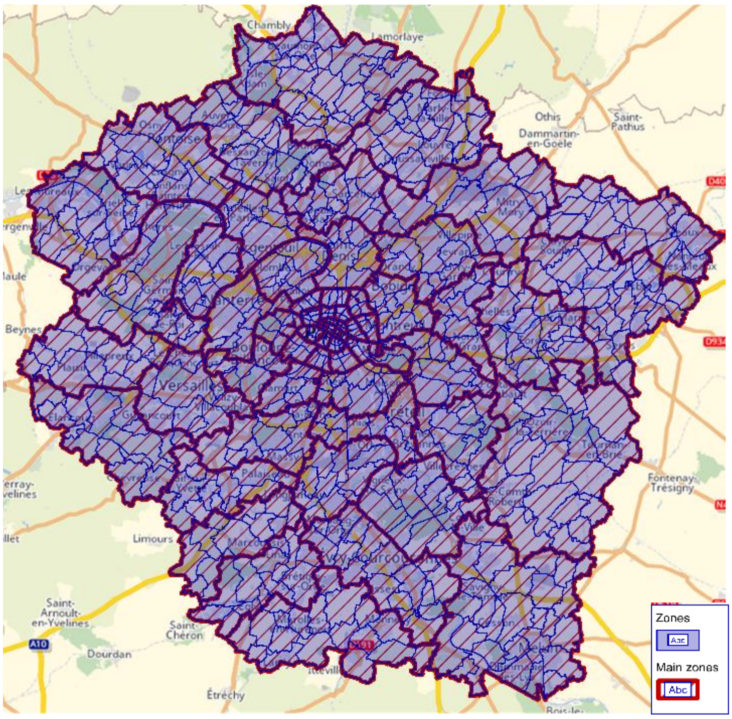

Figure 4 Zones and main zones of the study area.

4.9.4. Modal Split

One of the provided information in the result of agent-based model, and consequently in zone-based model, is the chosen mode of transport for each single trip. Therefore, the modal split for each demand stratum is computable. PuT, Car, Car-Passenger, and Walk are four modes of transport stated in the result. Modal split of these four modes of transport is comparable and almost close to the modal split state in (PDUIF, 2014) for Île-de-France.

Ground-taxi has been assumed as the main competitor for air-taxi and is not stated as a mode of transport for residents. Taxi is rarely considered as a mode of transport in the household travel survey. Therefore, there is not too much available resources as a reference to find the share of taxi in modal split for residents. To do a proxy with similar cities, some researches have been done. For instance, it is stated,in a report that taxi has had a mode share of 1.49% in Greater London in 2017 (TfL, 2018). Based on (Conway, Salon, & A. King, 2018) the share of taxi highly depends on the metropolitan area size and level of household income in the U.S. The number of people using taxi in cities with more than 3 million population are 2.2 times higher than cities with 1-3 million population. Also, it is stated in (Harbering & Schlüter, 2020) that 14.1%, 49.6%, and 36.3% of taxi trips in Valley of Mexico belong to home to/from work trips, home to/from other trips, and not to/from home trips, respectively.

Demand Stratum	**Modal Split**				
	Taxi	**PuT**	**Car**	**Car-Pax**	**Walk**
HBW_L	0.41%	42.7%	42.2%	2.4%	12.3%
HBW_H	0.76%	40.3%	44.8%	2.0%	12.2%
HBEDU_L	0.41%	29.3%	9.5%	14.1%	46.7%
HBEDU_H	0.76%	23.3%	11.8%	18.8%	45.3%
HBO_L	0.96%	11.4%	30.7%	10.2%	46.8%
HBO_H	2.05%	8.9%	36.1%	10.4%	42.5%
EDUBH_L	0.41%	29.3%	9.5%	12.9%	47.8%
EDUBH_H	0.76%	24.4%	12.8%	13.8%	48.2%
EDUBO_L	2.58%	15.2%	9.3%	6.8%	66.1%
EDUBO_H	5.07%	7.0%	9.8%	8.0%	70.1%
WBH_L	0.41%	41.1%	42.5%	3.9%	12.1%
WBH_H	0.76%	37.9%	45.9%	4.5%	10.9%
WBO_L	2.58%	27.4%	40.4%	3.6%	26.0%
WBO_H	5.07%	19.9%	44.7%	3.7%	26.6%
OBH_L	0.96%	11.9%	31.7%	10.2%	45.2%
OBH_H	2.05%	9.8%	35.8%	10.9%	41.4%
OBW_L	2.58%	21.0%	38.8%	2.9%	34.7%
OBW_H	5.07%	15.2%	48.1%	3.1%	28.6%
OBO_L	2.58%	13.4%	37.8%	11.2%	35.0%
OBO_H	5.07%	8.9%	38.7%	12.8%	34.5%

Table 15 Residents modal split.

Using a proxy from the mentioned references, some assumptions and calculations have been taken to find the share of taxi. First of all, it has been assumed that 1.5% of all trips have been done by taxi, in which high-income residents are twice as likely as low-income to use taxi. Secondly, the stated shares in (Harbering & Schlüter, 2020) for different types of trips have been taken into account, 14.1%, 49.6%, and 36.3% of taxi trips belong to home to/from work trips, home to/from other trips, and not to/from home trips. In addition, it has been assumed that taxi is as part of PuT and its share derived from PuT share. Table 15 depicts the modal split for residents including the taxi share.

4.9.5. Value of Time

Meuniera and Quinet (Meuniera & Quinet, 2015) has been assessed the value of travel time for French people, as well as for the residents of Île-de-France, Table 16. This study, which is for 2010, illustrates the VoT for home-workplace/school and other (shopping, leisure, visits, …). Using the inflation rate from 2010 to 2019, the relevant values for 2019 have been calculated. Moreover, the relevant values for low-income and high-income residents have been computed using extrapolation. Table 17 shows the taken values of travel time for residential model.

Trip purpose	**France**	**Île-de-France**
Professional	17.5	22.3
Home-workplace/school/day0nursery	10.0	12.6
Other (shopping, care, visit, leisure, tourism, etc.)	6.8	8.7
No reason given	7.9	10.7

Table 16 Urban values of time, all modes (in €2010/h in 2010) (Meuniera & Quinet, 2015).

Demand Stratum	**VoT (€)**	
	Low-Income	High-Income
HBW/WBH	7	21
HBEDU/EDUBH	7	21
Other Trips	5	16

Table 17 Value of travel time for residents.

5. Model development

This chapter contains the approach with which some procedures have been done to process derived data from the previous chapter to make them implementable for mode choice calculations. First, it is explained how the trips have been distributed for different models. In the second part, it is described the procedures in which the mode choice functions have been elaborated. Finally, the desired variables affecting the UAM demand for the current thesis have been delineated.

5.1. Transportation Model

As mentioned earlier, PTV VISUM has been used as the modelling software for the current study. Three demand models have been developed which are Airport model, Touristic model, and Residential model. First three steps of well-known four-step transportation model have been followed in this study. As the goal of this study is to find the potential demand for air-taxi service, there has been no need to do the traffic assignment step, which is the fourth step. Moreover, having the timetable and capacity of air-taxi vehicles is another reason has resulted in not using the fourth step. Last but not least, there has been no interest to find traffic assignment for other modes of transport, and therefore, it has been out of the scope of this study. In the following it is explained that how different models have been developed.

5.2. Trips Generation and Distribution

5.2.1. Airport Model

This step has been already done as all trips are originating or attracting by airports, it has been already explained in section 4.7.3. Airports are the origin or destination of all trips, and all trips have a trip rate of unit. Therefore, defining a utility function of unit (1) for trip distribution, the relevant zone-zone trips matrices have been created. These matrices show how many passengers are traveling between each pair of zones. For the airport model, for example, considering the trips to airport, those columns (zones) have values that CDG or Orly airport is located in, and other columns' cells have the value of zero.

5.2.2. Touristic Model

Three types of trips have been defined for tourists: Hotel-Attraction (HA), Attraction-Attraction (AA), and Attraction-Hotel (AH). The processes in which the trip rate of each type of trip has been calculated are explained in the following.

Daily activities for all demand strata have been calculated by the data available in touristic dataset (CRT, 2019). It has been assumed that daily activities equal to number of times that tourists of each demand stratum have left the hotel, and consequently equal to number of times that tourists have returned to the hotel. Therefore, these values are trip rates for HA and AH trips. These rates vary from 0.5 to 1.4 for different demand strata, for example personal international trips have the highest rates. Knowing HA and AH rates, the total number of HA and AH trips have been calculated. Regarding AA trips, a trip rate of 2 for this type has been assumed, except for tourists visiting Département 77 and 78. It has been assumed that tourists visiting Disney Land and Versailles have smaller AA trip rates, 0.8-0.85. Visiting these two places take more time than other attractions in Île-de-France. Moreover, these two attractions are located fare away from other attractions in Île-de-France which makes it less possible for tourists to visit other attractions in the same day. The taken rates are comparable with taken trip' rates in a study in which the author have modeled touristic trips in the province of Salzburg (Hofer, Haberl, & Fellendorf, 2016). In the mentioned study, the trip rate for HA, AA, and AH trips have been 0.828, 1.709, and 0.828, respectively. Therefore, the total number of produced and attracted trips from/by each zone have been calculated for all zones.

In the next step, the trips have needed to be distributed between zones. To be more specific, the number of trips between each pair of zones have been calculated. As mentioned earlier, tourists are very sensitive toward trip's distance and choose the attractions around the accommodation place (Jin & Xu, 2018). Therefore, a trial-and-error approach within a loop including trip generation and distribution procedure has been done to find the best utility function for trip distribution. Some modifications have been done during this process. First, attractivity and productivity of Département 77 and 78 for tourists staying in these two Départements have been considered much higher than other tourists, for instance most of tourists visiting Disney Land coming from the surrounding zones. Second, it has been assumed that tourists staying in Départements 77 and 78 have smaller AA trips' rates, which means it is less likely for those tourists to travel to far zones in the same day. Last but not least, distribution's utility functions have been modified to find the best fit, which means least possible error. Taken into consideration all the mentioned above assumptions, the trips have been distributed with an initial utility function. From other hand, the number of visitors for zones have been already known. Therefore, the results of distribution procedure have been compared with the number of visitors per zones. For example, for HA trips it is more likely for tourist to travel longer than AA trips, and, also, tourists staying in Départements 77 and 78 are willing to travel shorter than those staying in Départements 75. Therefore, the trips between all pairs of zones for all demand strata have been calculated.

5.2.3. Residential Model

As explained in 4.9.3, the trips have been already distributed for this model, the trips matrices for all demand strata have been available.

5.3. Mode Choice

The same approach has been followed in mode choice calculation for all models. The relevant modes, as explained in 4.7.4, 4.8.4, and 4.9.4, for each mode and demand stratum have been taken into account. As explained in 2.4, there are different attributes affecting mode choice behavior of travelers. The utility function for each mode is usually a combination of different attributes:

$$U_m = ASC_m + \beta_1 . X_{1m} + \beta_2 . X_{2m} + \cdots$$

(3)

Where U_m is the utility of mode m, X_{nm} is the relevant attribute for mode m, β_n is the coefficient for attribute n, and Alternative Specific Constant (ASC_m) is representative for all other aspects of mode m which have not been considered. In other words, β_m shows how important is attribute of mode m for corresponding demand stratum, and ASC_m depicts how is attitude of corresponding demand stratum toward mode m regardless of other attributes.

In the current study, some attributes depending on the mode have been taken into account along with ASC. For instance, the utility function for Car is as following:

$$U_{Car} = ASC_{Car} + \beta_{TT} . TT_{Car} + \beta_{Cost} . Cost_{Car} + \beta_{TTR} . TTR_{Car}$$

(4)

Where TT and TTR are travel time and travel time reliability, respectively.

Then dividing equation (1) by β_{TT} to bring the utility function into the unit of time:

$$\frac{U_{Car}}{\beta_{TT}} = \frac{ASC_{Car}}{\beta_{TT}} + 1 . TT_{Car} + \frac{\beta_{Cost}}{\beta_{TT}} . Cost_{Car} + \frac{\beta_{TTR}}{\beta_{TT}} . TTR_{Car}$$

And we will have:

$$U_{Car} = ASC_{Car} + 1 . TT_{Car} + \frac{\beta_{Cost}}{\beta_{TT}} . Cost_{Car} + \frac{\beta_{TTR}}{\beta_{TT}} . TTR_{Car}$$

(5)

The value of time and value of reliability are:

$$VOT = \frac{\mathrm{Cost}}{\mathrm{Time}}$$

(6)

and:

$$VOR = \frac{\mathrm{Cost}}{Time_{Reliability}}$$

(7)

The unit of β_{Time}, $\beta_{\mathrm{Time\text{-}Reliability}}$ and β_{Cost} are 1/Time, 1/Time-Reliability and 1/Cost, respectively, therefore:

$$\frac{\beta_{Cost}}{\beta_{TT}} = \frac{1/\mathrm{Cost}}{1/\mathrm{Time}} = \frac{\mathrm{Time}}{\mathrm{Cost}}$$

(8)

and:

$$\frac{\beta_{TTR}}{\beta_{TT}} = \frac{1/Time_{Reliability}}{1/Time} = \frac{Time}{Time_{Reliability}}$$

(9)

From equations (6) and (7) that $Time = \frac{\mathrm{Cost}}{\mathrm{VOT}}$ and $Time_{Reliability} = \frac{\mathrm{Cost}}{VOR}$, and by replacing in equation (8):

$$\frac{\beta_{Cost}}{\beta_{TT}} = \frac{\mathrm{Time}}{\mathrm{Cost}} = \frac{\mathrm{Cost/VOT}}{\mathrm{Cost}} = \frac{1}{\mathrm{VOT}}$$

(10)

and in equation (9):

$$\frac{\beta_{TTR}}{\beta_{TT}} = \frac{1/Time_{Reliability}}{1/Time} = \frac{Time}{Time_{Reliability}} = \frac{\mathrm{Cost/VOT}}{\mathrm{Cost/VOR}} = \frac{\mathrm{VOR}}{\mathrm{VOT}}$$

(11)

From equation (1) where $RR = \frac{VOR}{\mathrm{VOT}}$ and replacing in equation (11):

$$\frac{\beta_{TTR}}{\beta_{TT}} = RR$$

(12)

Where value RR is reliability ratio explained in page 16. Replacing equations (10) and (12) into equation (5):

$$U_{Car} = ASC_{Car} + 1\,.TT_{Car} + \frac{1}{\mathrm{VOT}}.Cost_{Car} + RR.TTR_{Car}$$

(13)

As explained in the previous sections, VOT for all demand strata and RR have already been calculated.

Following are the utility functions for all modes:

$$U_{Car} = ASC_{Car} + 1\,.TT_{Car} + \frac{1}{\mathrm{VOT}}.Cost_{Car} + RR.TTR_{Car}$$

$$U_{CarDrop} = ASC_{CarDrop} + 1\,.TT_{CarDrop} + \frac{1}{\mathrm{VOT}}.Cost_{CarDrop} + RR.TTR_{CarDrop}$$

$$U_{Taxi} = ASC_{Taxi} + 1\,.TT_{Taxi} + \frac{1}{\mathrm{VOT}}.Cost_{Taxi} + RR.TTR_{Taxi}$$

$$U_{PuT} = ASC_{PuT} + 1\,.TT_{PuT} + \frac{1}{\mathrm{VOT}}.Cost_{PuT}$$

$$U_{Walking} = ASC_{Walking} + 1\,.TT_{Walking}$$

$$U_{MM} = ASC_{MM} + \beta_{InAir}.TT_{InAir} + 1\,.TT_{MM-InAir} + \frac{1}{\mathrm{VOT}}.Cost_{Taxi} + RR.TTR_{Feeder}$$

Where MM is multimodal mode, InAir is the time spending in air-taxi while flying, and TTR_{Feeder} is the congestion factor for the feeder (Taxi) of access/egress part of the trip.

It has been assumed that the coefficient of Travel Time, Congestion, and Cost for all modes are equal. In addition, the impact of congestion (via RR) has been considered for Car, CarDrop, Taxi, and feeder of Multimodal mode. All the attributes, and coefficients for the utility functions of different modes have been already calculated and ready to be employed, except for ASC of different modes. To find ASCs, Demand Calibration function in PTV VISUM has been used.

Utility function determines the utility of each mode, and consequently the share of each mode. However, in the current study the modal slit is available for all existing modes except MM. Therefore, an inverse approach has been followed. In Demand Calibration procedure in PTV VISUM, the model tries different ASCs for each mode of transport so as to match actual modal split with the target modal split and make the error between the actual modal split and target as close as to zero. In the current study, more than 1200 iterations for each of three models have been run to reach errors less than 0.00001 for all modes of different models. It needs to be mentioned that each demand stratum has one unique ASC for each mode of transport, e.g., total number of ASCs equal to multiplying number of demand strata by corresponding modes.

The only absent parameter in the mode choice utility functions is ASC_{MM}, as MM is not an existing and observed mode. Looking into the literature, several SP surveys have been done to find ASC for UAM (Fu (2), 2018; Boddupalli, 2019). Furthermore, some studies have assumed that ASC of air-taxi/UAM is equal to ASC of some other modes. For instance, in a study it has been assumed that ASC of air-taxi is similar to Rideshare mode (Rimjha (1), Hotle, Trani, Hinze, & Smith, 2021). However, Balac et al. have assumed that UAM and taxi have the same parameters as PuT (Balac, Rothfeld, & Hörl, 2019). In the current study it has been assumed that ASC_{MM} equal to ASC_{Taxi}.

Therefore, having calculated the utility of each mode for each demand stratum using utility function and explained parameters and skim matrices, the developed model has been ready to run and calculate the UAM potential demand for each of three models.

5.4. Model Variables

As explained in section 3.2, there are different factors that could affect the UAM usage. Therefore, for the current work some factors have been considered as the model' variables with which different scenarios could be defined. The variables are as following:

- **Peak hour:** to see the impact of peak hour, the main contribution for travel time, two sets of analysis have been done. First, the average travel time during the day has been considered as the base case. Secondly, the travel time in morning peak hour which shows the impact of congestion have been taken into account.
- **Target group:** as explained earlier, there are three different models in this study and the behavior of passenger of each model is different than the other one. Therefore, the potential demand of each model needs to be assessed separately. These models are:
  - Airport Model
  - Touristic Model
  - Residential Model
- **Network density:** this factor has been assessed using different number of stations, consequently number of routes, within the network in the earlier studies (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021; Fu (1), Straubinger, & Schaumeier, 2020; Rimjha (2), Hotle, Trani, & Hinze, 2021). As explained in section 3.1, four different levels have been selected for this study:
  - 18 UAM lines
  - 36 UAM lines

- 74 UAM lines
- 118 UAM lines

- **Headway:** UAM in the current study is timetable-based. Different headways have been defined, which are constant for all the UAM lines. These values have been selected after having discussed with internal vertiport and UAM operation specialists from Volocopter.
  - 10 minutes
  - 20 minutes
  - 30 minutes
- **Air-taxi speed:** although cruising speed is not one of the factors significantly affecting the UAM according to what have seen in the literature, in the current study two speed levels have been chosen to check the impact of air-taxi vehicle cruising speed.
  - 60 km/hr
  - 80 km/hr
- **UAM base-fare:** the levels of this parameter vary from 0 to 200 € with step of 25 €, see Table 18.
- **UAM distance-based fare:** the levels of this parameter range from 0 to 9 €/km with step of 3 €/km, see Table 18.

Combination	Fare (€-€/km)		Combination	Fare (€-€/km)	
	Base	Distance-base		Base	Distance-base
1	0	3	11	75	0
2	0	6	12	75	3
3	0	9	13	75	6
4	25	0	14	100	0
5	25	3	15	100	3
6	25	6	16	125	0
7	25	9	17	125	3
8	50	0	18	150	0
9	50	3	19	175	0
10	50	6	20	200	0

Table 18 Selected subsets of possible combination for UAM fare.

Looking at earlier works, it is discernible that the authors have selected relatively much lower fare values in comparison to chosen values in the current study. Rimjha et al.

(Rimjha (2), Hotle, Trani, & Hinze, 2021) have considered distance-based fare of 1-3 $/mile. In another study base-fare and distance base-fare range 3-60 CHF and 0.6-4.2 CHF/km, respectively (Balac, Rothfeld, & Hörl, 2019). Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have considered base-fare and distance-based fare between 0-10 € and 1-10 €/km, respectively. After having discussed with the commercial and operational specialist from Volocopter, it has been found that the UAM fare will not be as low as what have used in the mentioned studies, at least for the first years of UAM operation. Therefore, different values have chosen for UAM fare.

As some combinations of base fare and distance-based fare could be resulted in very high fare for air-taxi, for instance combination of 200 € and 9 €/km, a sub-set of all possible combinations have selected. Table 18 Shows the selected combinations of fare-base and distance-based fare.

- **<u>Access time to vertiport:</u>** as explained in section 3.2.7, this factor presents access/egress via walking mode. This factor highly depends on the network density. For the current study, two levels for access/egress time have been chosen:
  - 5 minutes
  - 10 minutes
- **<u>Processing time:</u>** Balac et al. (Balac, Rothfeld, & Hörl, 2019) have assumed that processing time ranges between 0-12 minutes. In another study, this factor is between 0-20 minutes (Fu (1), Straubinger, & Schaumeier, 2020). For the current study, after having received consultation from vertiport specialists at Volocopter, it has be found that with the current configuration of vertiport, the minimum processing time will be around 12 minutes. Therefore, two levels for this attribute have been chosen, the base case and improved case.
  - 12 minutes
  - 6 minutes
- **<u>In-Vehicle time:</u>** during the first years of operation, being in a flying vehicle will probably have a fun aspect, particularly for tourists. Therefore, in-vehicle time factor could represent this aspect. In an earlier study, Peksa and Bogenbeger (Peksa & Bogenberger, 2020) have considered this factor as a representative attribute for comfortableness. Therefore, two values have been taken for this variable, the base case and improved case.
  - 1
  - 0.5

Table 19 shows as a summary of all selected levels for different attributes.

Attribute			Levels
Peak hour	2	-	No, Yes
Target group	3	-	Airport passengers, tourists, residents
Network density	4	UAM routes	18, 36, 74, 118
Headway	3	minutes	10, 20, 30
Air-taxi speed	2	Km/hr	60, 80
UAM base fare	9	€	(0,3), (0,6), (0,9), (25,0), (25,3), (25,6), (25,9), (50,0), (50,3), (50,6), (75,0), (75,3), (75,6), (100,0), (100,3), (125,0), (125,3), (150,0), (175,0), (200,0)
UAM distance-based fare	4	€/km	
Access/egress time	2	minutes	5, 10
Processing time	2	minutes	6, 12
In-Vehicle time coefficient	2	-	0.5, 1

Table 19 Models' input

6. Results

In this chapter the UAM potential demand under different scenarios are presented. In general, 3,840 scenarios have been run, in which the potential UAM demand for all three models have been calculated. Following in this chapter, the impact of different model's variables on the UAM potential demand are provided.

6.1. Headway

Figure 5 shows the UAM potential demand for different scenarios and under different headways in the peak hour. For all other parameters, the base cases have been considered, which are 0 €, 3 €/km, 60 km/hr, 10 minutes, 12 minutes, and 1 for fare base, distance-based fare, speed, access time, processing time and in-vehicle coefficient. As it can be seen, the UAM demand has not been changed in different headways. There are two explanations for these zero differences. First, it has been assumed that travelers manage to be at vertiport on-time and no waiting time due to unreliability of system has been assumed. Secondly, another possible impact of different headways could be a result of transfer time between two different lines of air-taxi, which longer headway resulting in longer waiting/transferring time. Looking at the UAM potential demand under different scenarios, it has appeared that there is almost no traveler used two lines of air-taxi in row. Therefore, the further analysis has been provided with the headway of 10 minutes.

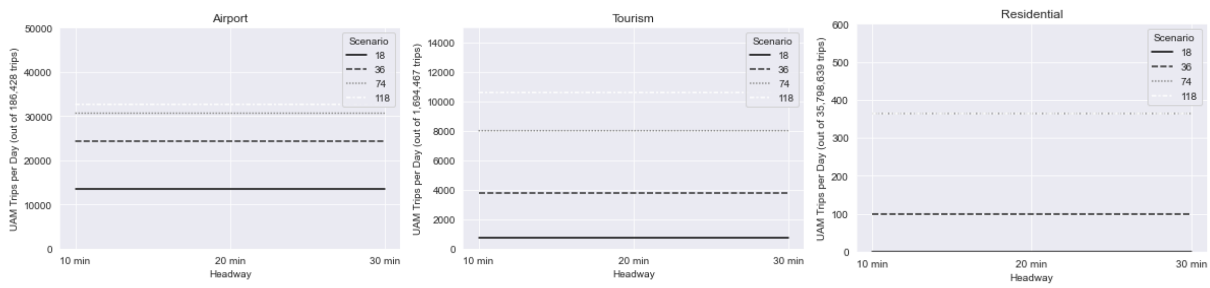

Figure 5 UAM potential demand in different scenarios under different headways.

6.2. Peak Hour

Figure 6 depicts the UAM demand for different models under different scenarios for peak and non-peak times. The impact of peak hour on airport model is highest, following by tourism model, and this impact is growing by increase in number of routes. However, not only peak hour travel time influences the UAM demand residential model least among all models, but also this impact is not changed significantly with different number of routes.

Speed	Access	Proc	In_vehicle	Fare km	Fare base	Headway
60	10	12	1	3	0	10 min

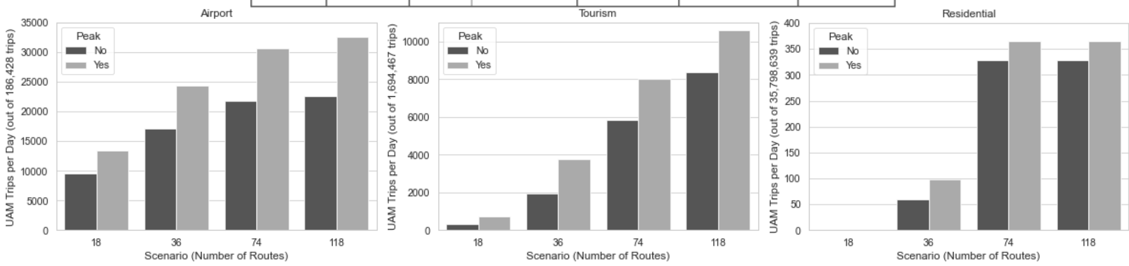

Figure 6 UAM potential demand under different scenarios for peak and non-peak time.

6.3. Fare

Figure 7 a) shows UAM demand in different distance-based fare (Fare-km) schemes. The bars show that all models are too sensitive to change in fare-km. Although the UAM demand for airport model is drastically reduced in fare-km of 6 and 9 €/km, there are still some passengers being willing to use UAM. However, there is no demand for tourism and residential model for fare-km of 9 €/km and 6-9 €/km, respectively. In addition, sensitivity to fare-km highly depends on the number of routes. Considering the residential model, there is no UAM demand for 18 UAM lines scenario, even for a fare-km of 3 €/km, but UAM demand is increased significantly from 36 routes to 74/118 routes. Also, it is discernible that increasing the number of lines from 74 to 118 does not add any initial interest to attract more passengers in residential model, for a distance-based fare of 3 €/km. Despite that, increasing the density of UAM network has significant impact on UAM demand for airport and tourism models, particularly when number of lines increasing from 18 to 36 and from 36 to 74.

Figure 7 b) depicts UAM potential demand for different air-taxi base fares. All three models show a very high level of sensitivity to increase of base-fare. However, despite the fact that UAM demand is increasing significantly while base-fare is getting more expensive, there are still some demand even for a ticket price of 200 €. But there will not be any demand for tourism and residential model when the base-fare is going higher than 75 € and 25 €, respectively. For the base fare of 25 €, the UAM demand in residential model is increased when the number of lines is increasing, but there is no demand for more expensive base-fare even with higher number of lines. Regarding airport model, passengers are less sensitive to the number of routes in cheaper base-fare than higher ones. For instance, UAM demand for base-fare of 25 € is increased by 33% from 18 routes to 118 routes scenario, and this change for base-fare of 100 € is more than 1300%, and for base-fare of 150 € is grown from 0 to 17 trips. The trend for tourism model is not changing as significant as airport model. To be more specific, increasing from 18 routes to 118 routes scenario in touristic model, UAM demand for base-fare of 25 € and 75 € are expanded 157% and 126%, sequentially.

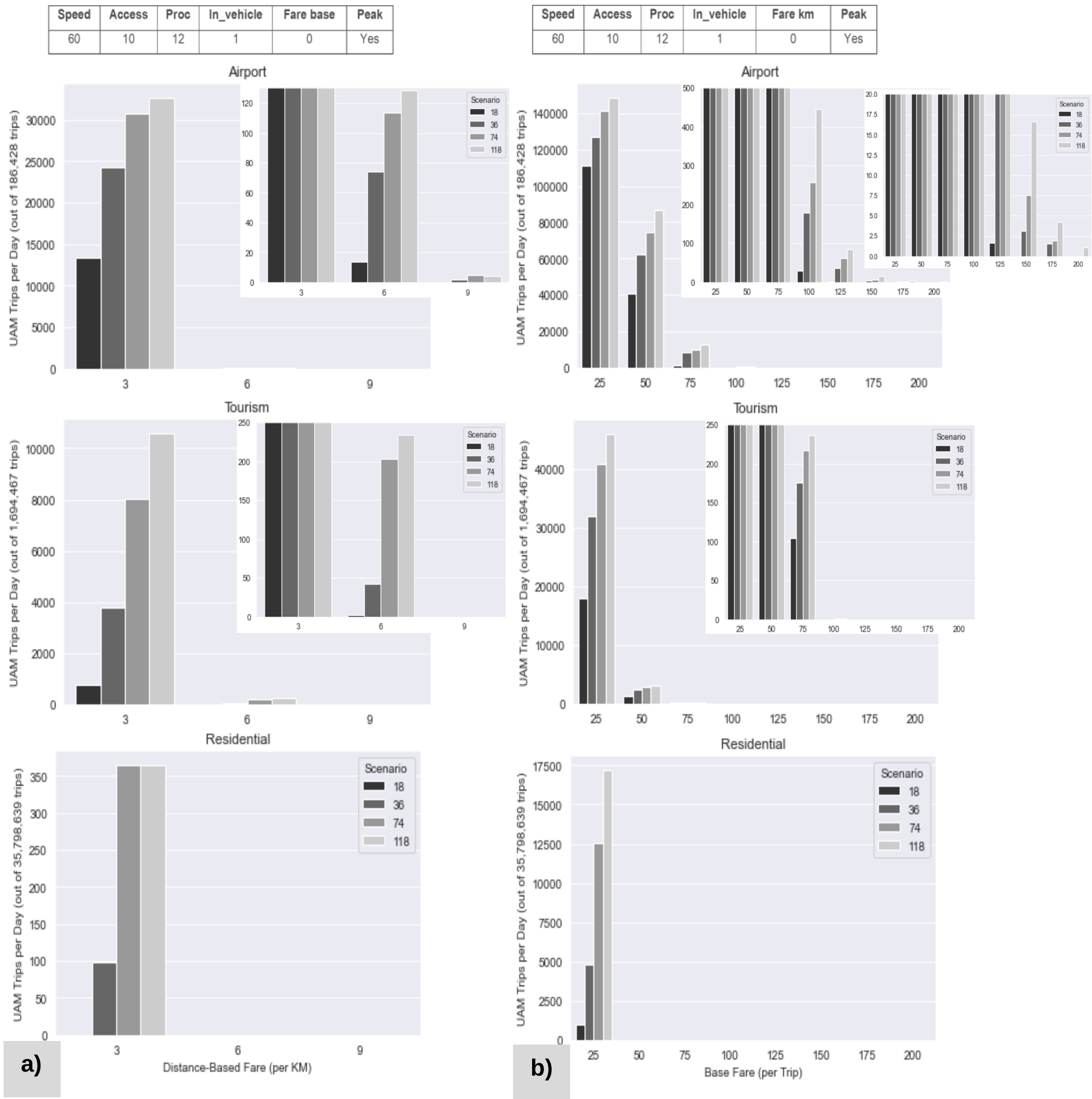

Figure 7 UAM potential demand under different scenarios and a) different distance-based fare, b) different base fare.

Figure 8 illustrates the UAM demand in different fare combinations, see Table 18, for scenario 118 routes. As explained earlier, the residents are the most sensitive groups to the fare. There is no potential demand in residential model for none of the combinations, except for the combination of (0, 3), and (25, 0). The demand for later combination is much higher because this fare scheme is independent of distance and is comparable to other convenient modes like taxi in terms of travel cost. For tourism model, there are more combinations whose attract some tourists, (25, 0) has the highest UAM demand following by (0, 3), (50, 0), (25, 3), (75, 0), and (0, 6). The only combination including both base-fare and distance-based fare are (25, 3) which interestingly attracts more demand than (75, 0) and (0, 6). Last but not least, airport model has UAM potential demand for a wider range of fare combinations. (25, 0) is considerably attractive for most of airport passenger. Interestingly and despite of tourism model, (50, 0) scheme is much more popular than (0, 3) for airport passengers. Figure 9 shows the popularity of different fare combinations for airport passengers.

Looking at Figure 8 and comparing two fare schemes of (25, 0) and (0, 3) which are totally different, it is discernible that UAM demand for (25, 0) is 4-5 times higher than (0, 3) for airport and tourism model, however this ratio for residential model is more than 47 times. This could be concluded that residents are willing to pay for constant ticket rather than distance-based ticket.

Speed	Access	Proc	In_vehicle	Scenario	Peak
60	10	12	1	118	Yes

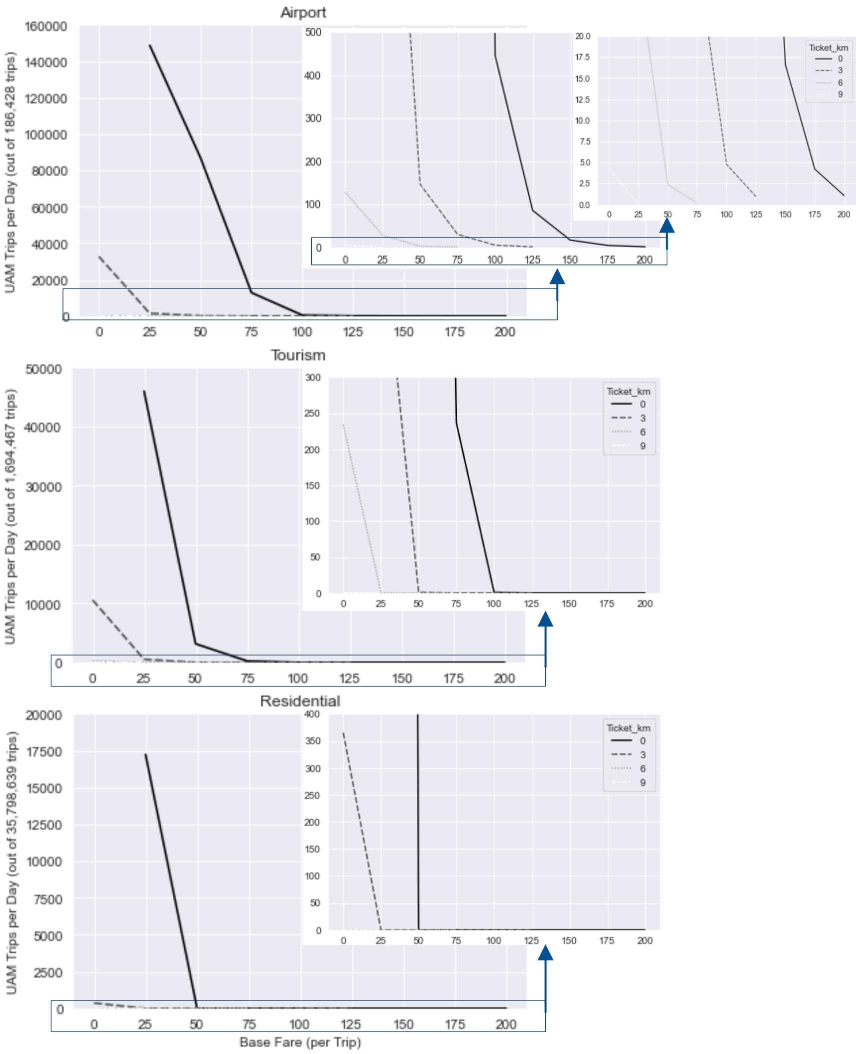

Figure 8 UAM potential demand under different scenarios and fare combinations.

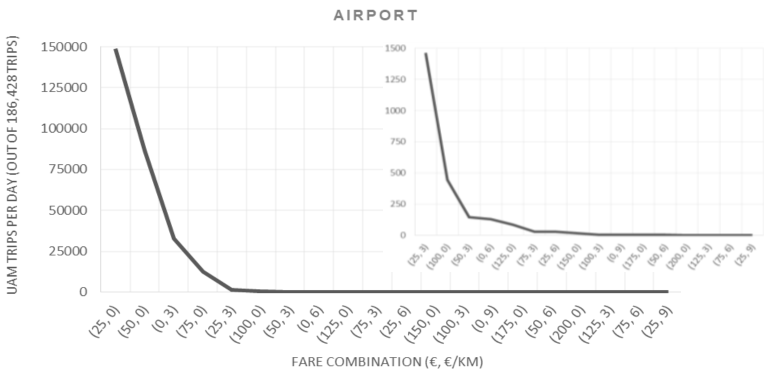

Figure 9 UAM demand of airport model under different fare combination.

6.4. Access Time

Figure 10 depicts the impact of a change in access time on UAM potential demand for different models. The growth of UAM demand in airport model under shorter access time for fare of 3, 6, and 9 €/km are 37%, 88%, and 299%, respectively. The corresponding ratios for tourism model are 48% and 184% for fare of 3 €/km and 6 €/km, and in residential model is 235% for the fare of 3 €/km. Airport model with a distance-based fare of 3 €/km is affected the least, because the low-ticket price of UAM for this group of travelers is too cheap and much more attractive than other modes. Notwithstanding, the fare of 9 €/km, which is an expensive ticket price, in airport model is affected the most because the travel time would be the determining factor for the passengers being willing to accept this ticket price. However, the fare scheme of 3 €/km which is considered too expensive for residents is affected significantly by halving the access time. Although the UAM potential demand for residential is increased by 235%, there is still no potential demand for the fare of 6 and 9 €/km. However, the impact of lower access time for base-fare is getting more influential for ticket prices more than 50 € in airport and tourism model. But for residential model the impact of shorter access time on the base-fare of 25 € is not as significant as the impact on the distance-based fare of 3 €/km, 35% vs. 235%.

6.5. Speed

Figure 11 illustrates the UAM potential demand under different speeds and distance-based fares for three models. 20 km/hr difference of speed does not impact the UAM potential demand as significant as access time, as the difference is not enough to have a determining influence. However, the impact of speed is increasing as the fare is rising. Among all, the highest change with 135% growth occurs for airport model and the fare of 9 €/km, and the smallest for residential model with 13% increase. Similarly, the impact of speed is getting more influential with any increase of base-fare, where the difference in airport model for the base fare of 25 € and 100 € are 3% and 17%.

Speed	Proc	In_vehicle	Fare base	Scenario	Peak
60	12	1	0	118	Yes

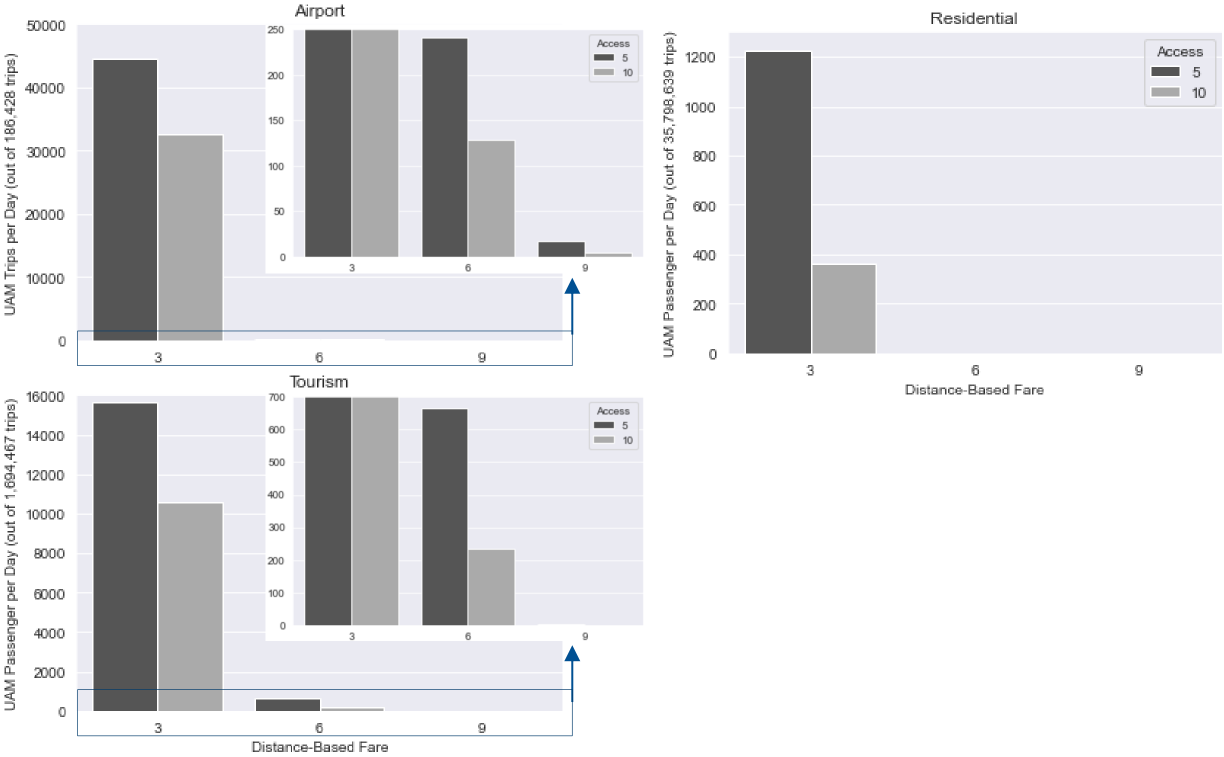

Figure 10 UAM potential demand under different access time.

Proc	Access	In_vehicle	Fare base	Scenario	Peak
12	10	1	0	118	Yes

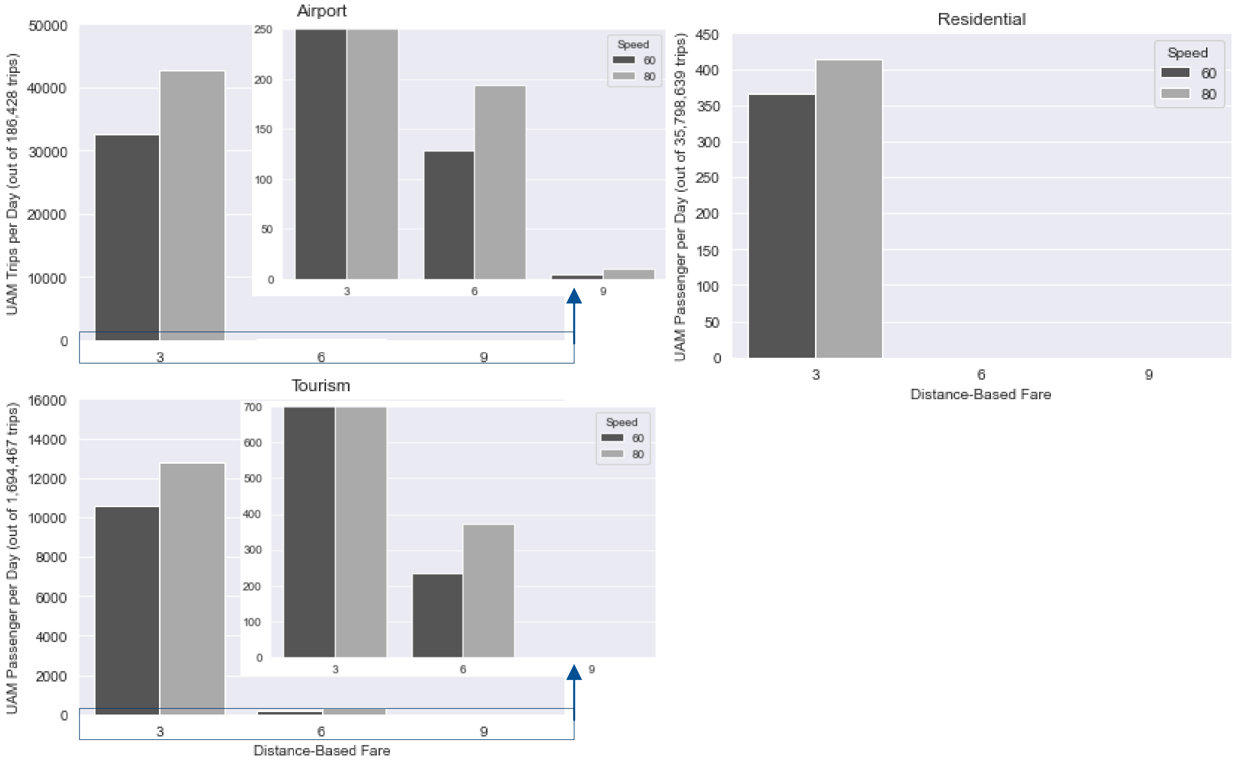

Figure 11 UAM potential demand under different speed.

6.6. Processing time

Figure 12 shows the impact of halving the processing time on the UAM potential demand. This attribute is as influential as access time and more significant than speed. Processing time and access time are both determining the travel time and have the same coefficient, based on this study assumptions. Therefore, they affect the UAM similarly. Alike other attributes, the impact of processing time is increase when the fare is rising. Considering airport model, the UAM potential demand increase by 35%, 89% and 239% for distance-based fare of 3 €/km, 6 €/km, and 9 €/km. As it can be seen, the impact of halving processing time is significantly higher for the fare of 9 €/km, rather than other fare schemes. The corresponding change for tourism model is 48% and 157% for fare of 3 €/km and 6 €/km, and 103% for residential model. Highest impact in ticket price of 3 €/km occurs for residential model following by tourism model. Likewise, processing time influence in fare of 6 €/km in tourism model is higher than airport model. Comparing two fare schemes of (25, 0) and (0, 3) for residential model, it could be found that the distance-based fare of 3 €/km is affected by processing time more than constant fare of 25 €, 103% versus 22%. When travel time is reducing, consequently as a result of decreasing the processing time, UAM starts defeating other modes of transport in shorter trips, in which processing time is a considerable portion of travel time.

6.7. In-Vehicle coefficient

Figure 13 illustrates the impact of in-vehicle coefficient on the UAM potential demand for different models. Clearly, the impact of this attributes is getting higher by increasing the fare. For instance, halving the in-vehicle coefficient results in 63%, 112% and 280% growth of UAM demand for distance-based fare of 3 €/km, 6 €/km, and 9 €/km, respectively in airport model. Generally, airport model and fare of 9 €/km is affected the most with 280% growth, and tourism model with the fare of 3 €/km experiencing 41% increase in UAM demand is influenced less that all other states. Comparing the change of UAM demand between different models, it has appeared that the impact of this change is somehow similar for all models in the same distance-based fare, e.g., in the fare of 3 €/km the change is 63%, 41%, and 54% for airport model, tourism model, and residential model, respectively, and in the fare of 6 €/km is 112% and 119 for airport and tourism model. However, regarding base fare schemes, in the same fare, the residential model is affected the most following by tourism model.

Speed	Access	In_vehicle	Fare base	Scenario	Peak
60	10	1	0	118	Yes

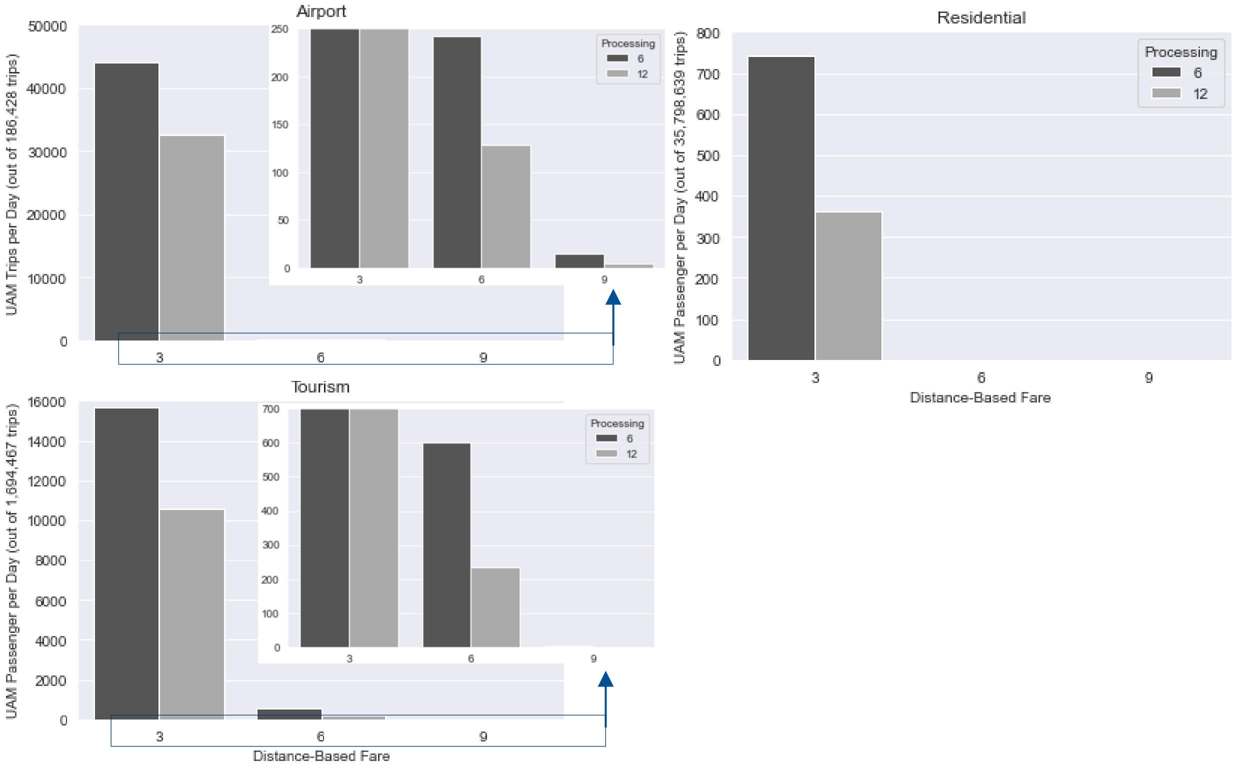

Figure 12 UAM potential demand under different processing time.

Speed	Access	Proc	Fare base	Scenario	Peak
60	10	12	0	118	Yes

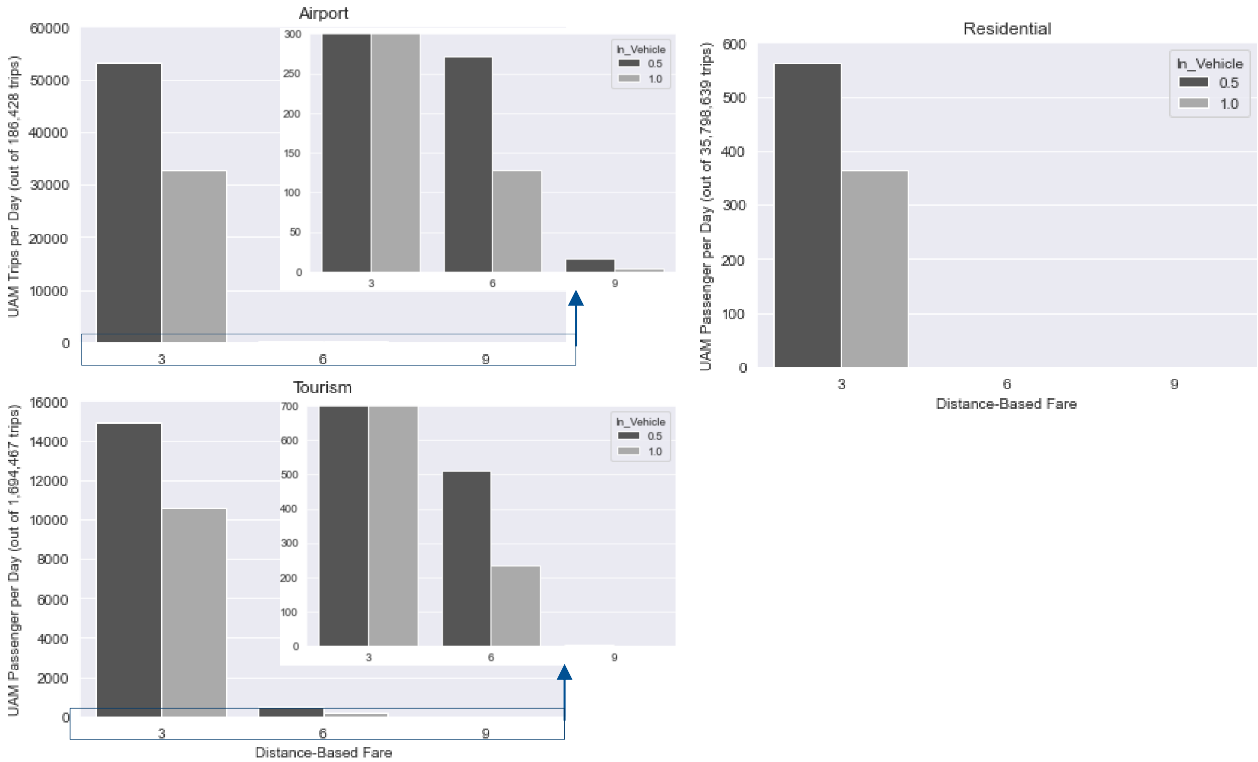

Figure 13 UAM potential demand under different In-Vehicle coefficients.

6.8. Cross impact of variables

Appendix A-D include charts related to cross impact of fare, scenario, and pick hour with other variables for three models. In each appendix for all other variables which are not mentioned the base case has been considered.

Despite to very high number of trips in residential model in comparison to other models, a trivial portion of UAM potential demand belongs to residential model, in the best case the mode share of UAM is 0.117%. Expect for two fare schemes which are (0, 3) and (25, 0), UAM is not attractive for resident at any extent. The only exception occurs in fare scheme of (50, 0) and with best case values for all attributes in which a few trips are attracted by UAM.

For almost all the fare schemes, majority of UAM potential demand belong to airport model, except for (0, 6). As airport trips are predominantly long-distance trips, this fare scheme which is 6 €/km is too expensive. In contrast, for tourists which are willing to have shorter trips, this fare scheme would be more attractive than airport passengers.

Comparing Appendix A and Appendix B, it can be found that the impact of access time and processing time are affecting UAM demand similarly. However, access time is getting slightly more influential when the fare combinations are going to be more expensive. Contrasting the difference between the impact of access time and speed, Appendix A vs. Appendix C, access time seems to be more influential. Following this, it can be found that access time are more significant than speed rather than constant fare combinations in fare combinations including distance-based fare. Following this, for constant fare combination of (25, 0) and (50, 0), the importance of these two attributes is almost equal. However, the access time is again getting more significant for more expensive constant fare. Setting side by side Appendix A and Appendix D, access time vs. in-vehicle coefficient, it is clear that in-vehicle coefficient affects UAM demand more than access time in almost all fare combinations for airport passengers. However, the situation for tourism model is different. For tourism model, the access time is more significant than in-vehicle coefficient for the cost combinations including distance-based fare, and, on the contrary, in-vehicle coefficient is more significant for constant fares.

Comparing Appendix B and Appendix C, it can be stated that undoubtedly processing time is more important than speed for fare schemes including distance-based fare. However, speed is slightly more influential than processing time with constant ticket prices more than 25 €, particularly for airport model. Considering fare schemes of (25, 0) and (0, 3), the impact of these two attributes is almost equal for airport passengers, although processing time affects tourism model slightly more than speed in these fare combinations. Comparing Appendix B and Appendix D, processing time vs. in-vehicle coefficient, shows in-vehicle coefficient time is more influential than processing time in attracting passengers to UAM. Last but not least, in-vehicle coefficient contrary to speed has more influence on UAM demand.

7. Discussion and Main Findings

This chapter discusses the main findings of this thesis mostly according to different factors explained in the previous chapters. Moreover, some results are compared to corresponding results from literature.

7.1. Target group

As the results show airport passengers are the dominant potential users for UAM, so as there is a demand for any fare scheme, regarding UAM mode share. Considering total number of trips for all models which are “186,428”, “1,694,467”, and “35,798,639” trips per day for airport model, tourism model, and residential model, respectively. Although the number of airport trips is considerably lower than other models, this group of passengers has the highest absolute number of UAM trips for all fare schemes expect for (0, 6) for which tourists are dominant. It is discernible that even for very expensive fare combinations some airport passengers are willing to use UAM. It is because, firstly, airport passengers benefit of UAM more than other groups due to longer trips’ distances. Secondly, UAM’s cost is somehow comparable with the competitive mode which is taxi for airport-city and city-airport trips.

Followed by airport passengers, tourism model has also much higher absolute number of trips and mode share attracted by UAM rather than residents. As stated in the last paragraph, tourists are attracted by UAM even more than airport passengers in the fare combination of (0, 6).

Last but not least, although the total number of daily trips for residential model is more than 35 million, a few numbers of residents are willing to use UAM for the cheapest fare combination. There is no potential demand for residential model in different fare combinations other than (25, 0) and (0, 3), with which the mode share is only 0.11% and 0.01%, respectively, taking into account the best cases for all variables. However, there very few trips for (0, 6) when setting all variables to the base cases, the UAM demand is only 137 out of “35,798,639” daily trips. Rimjha et al. (Rimjha (2), Hotle, Trani, & Hinze, 2021) have investigated the UAM mode share for commuters in Northern California under different distance-based fares. Their result shows that the UAM mode share under the fee of 3 $/mile is around 0.05%, which the results and fare is comparable with the current study. It needs to be noticed that in the just mentioned study the fare of 3 $/mile is the most expensive fare scheme, although the fare of 3 €/km is the cheapest cost scheme among all distance-based combinations in the current study. Even though, with the fare of 1 $/mile the mode share in the mentioned study is around 0.9%, and, therefore, in a very cheap UAM the mode share for this mode of transport for residents is not still substantial.

To sum up, as depicted in Figure 1 and stated by Straubinger et al. (Straubinger, et al., 2020), the potential user in the short run with relatively expensive ticket price will be high-income people and businesses travelers which in the current study are high-income airport passengers.

7.2. Network density

Number of vertiports, or number of UAM routes, represents the network density. As stated in some of previous studies (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021; Rimjha (2), Hotle, Trani, & Hinze, 2021), the number of stations is one of the most influential factors determining the UAM demand. Number of vertiports highly affects the accessibility of UAM and increase the areas covered by UAM. In other words, increasing the number of vertiports, or number UAM lines, more travelers are able to access UAM network in an even shorter access time.

The impact of increasing the number of UAM lines in the current work is noticeable. Considering airport model, the potential UAM demand is increasing by raising the number of UAM lines. The change in UAM demand is more significant when the number of lines is grown from 18 to 36 rather than other growth when the fare scheme only include distance-based fare. On the contrary, in base-fare schemes and for tickets more expensive than 75 € the change in UAM demand is much higher from 74 lines to 118 than other changes. For tourism model, although the increase in number of lines results in more demand for UAM, the most substantial change occurs for the fare of (0, 6) when the number of lines changes from 36 to 74. Finally, there is almost no demand for the fare of (0, 3) when network includes 18 routes for the residential model. Interestingly, the potential demand for the mentioned fare schemes does not change when the number of lines increase from 74 to 118. However, the number of residents attracted by UAM increases by raising the number of UAM lines for the ticket price of 25 €.

7.3. Headway

As stated in section 2.4, most of previous works in the area of UAM have been modeled UAM as on-demand service. The only study which has been modeled UAM in a headway-based manner (Peksa & Bogenberger, 2020) has not assessed the impact of headway on the UAM usage. The result of current study illustrates that the change of headway will not affect the UAM demand. To be more specific, the UAM has been assumed as a mode of transport with a very high level of reliability, in which the passengers rely on the service and arrive at the vertiport on-time. Furthermore, as no trip with more than one flight has been seen, the change of transfer time between two UAM lines caused by different headway does not affect the travel time of multimodal mode in different headways. Considering relative short distance trips, which is the nature of urban mobility, and since short trips are very sensitive to travel time, extra processing time and transferring time between two UAM lines would make UAM unattractive and incomparable with other modes of transport. Therefore, the zero impact of change in headway seems to be logical. However, there should be some impact caused by different headways in terms of capacity constraints, which is out of the scope of current study.

7.4. Peak hour

Setting side by side the UAM demand in non-peak hour and peak-hour depicts that the airport model is affected most following by tourism model. Furthermore, the impact of peak-hour is getting higher by increasing the constant fare. In a previous study, Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have also stated the significant impact of demand during peak hours in comparison to non-peak hours. However, as the predicted UAM demand is for the whole network, it would be unreasonable to consider and provide service based on demand resulted from peak-hour travel time. Because Rimjha et al. (Rimjha (2), Hotle, Trani, & Hinze, 2021) has found that each peak hour trips for UAM are very unidirectional.

7.5. Fare

As mentioned earlier, it has been assumed that UAM cost in the first years of operation will not be as cheap as defined in the previous studies. Rath and Chow (Rath & Chow, 2019) have defined three scenarios of short-term, mid-term and long-term contributing to different air taxi prices, which short term has the highest price. Therefore, the determined fare schemes for the current thesis have tendency to medium and highest price as targeting the short-term and mid-term applications of UAM. In this study two cost attributes for UAM have been defined: Constant fare from 0 up to 200 € and variable fare from 0 up to 9 €/km. All three models show a very high level of sensitivity to change in fare scheme, either constant fare or variable fare. It has also been found that there is no demand for fares more than 3 €/km and 25 € for residential model, however, the demand for those two fare schemes is still too low and not considerable. In a previous study, in which has resulted in very low and not considerable demand for UAM in residential model, the maximum variable fare has been 3 $/mile (Rimjha (2), Hotle, Trani, & Hinze, 2021). However, the variable fare in this study starts from 3 €/km. Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have defined the distance-based fare up to 10 €/km and there are some demand for the fare of 10 €/km as well, but the commuters and airport passengers have been considered together so as the UAM demand is aggregated. Therefore, it is hard to differentiate between behavior of two group of passengers based on their result. From other hand, it seems that tourists have medium behavior between airport passengers and residents, so as they are willing to pay more than residents and less than airport passengers for UAM. This trend is also applicable in terms of constant fare for UAM. Comparing two fare schemes of (25, 0) and (0, 3), it is apparent that popularity of (25, 0) is 4-5 times higher than (0, 3) for airport and residential model. However, this ratio for residential model is more than 47 times. Although the UAM demand reduces by any increase in fare, there is still some demand for all fare combinations in airport model, and not for tourism and residential model. There is no demand for fare combination other than (25, 0) and (0, 3) in residential model. Considering the tourism model, (25, 0) is the most popular fare scheme following by (0, 3), (50, 0), (25, 3), (75, 0), and (0, 6). Interestingly, (25, 3) which includes both base-fare and distance-based fare is more popular than (75, 0) in tourism model, in contrast to airport model in which (75, 0) is more popular than the other one. This difference is due to the fact that the average length of tourists' trips is considerably shorter than airport model.

In general, it is readily apparent that the UAM is more influential to distance-based fare than constant fare. It has also been concluded by Balac et al. (Balac, Rothfeld, & Hörl, 2019) that doubling the base fare has a smaller negative influence on the demand than doubling variable costs.

7.6. Access time

Access time, which highly depends on the network density as well, could significantly affect the UAM demand as a travel time components and considering the most claiming advantage of UAM which is its time-saving nature. Straubinger et al. (Straubinger, et al., 2020) have introduced access time/waiting time as one of factors with highest relevance for being influential on UAM demand. In the current study, access time is relevant for those travelers who have access to vertiport via walking mode. Results of the current study show that halving the access time increases the UAM potential demand. The impact of access time is swelling when the (perceived) cost for UAM is rising. Perceived cost could be defined as being expensive or cheap for each target group. Considering distance-based fare, fare of 3 €/km is considered as a very cheap ticket price for airport passengers, although it is a relatively expensive for residents. Respectively, fare of (0, 9) in airport model, fare of (0, 3) in residential model, and fare of (0, 6) in tourism model have been increased UAM demand by 299%, 235%, and 189% when access time is halved. However, comparing two fare schemes of (0, 3) and (25, 0) in residential model, as there is more UAM potential demand for (25, 0), which means this fare is perceived as cheaper, the impact of shorter access time on the base-fare of 25 € is not as significant as the impact on the distance-based fare of 3 €/km, 35% vs. 235%. Similarly for airport, the ticket price of 25 € and 50 € are much more popular, see Figure 9, than the fare of 3 €/km in airport model. Therefore, the impact of shorter access times is resulted in increase of 3%, 14%, and 37% for the fare of (25, 0), (50, 0), and (0, 3), sequentially. To be more specific, the impact of access time is getting higher by increasing the UAM cost.

7.7. Speed

Speed is not considered as a factor affected UAM significantly. However, speed is still an affecting factor as it impacts travel time directly. Balac et al. (Balac, Rothfeld, & Hörl, 2019) have stated that cruise speed has a non-marginal effect on the UAM demand. Concretely, an increase in cruising speed from 60 km/h to 120 km/h has a stronger effect on the number of trips than an increase from 120 km/h to 240 km/h. From other hand, Fu et al. (Fu (1), Straubinger, & Schaumeier, 2020) have concluded that changing the cruise speed from 50 km/hr to 350 km/hr has just increase the UAM trips around 20%. The results of current thesis show that 20 km/hr difference of speed does not impact the UAM potential demand as significant as access time, taking into account this fact that both attributes determine UAM travel time since the speed change is not enough to have a determining influence. However, the highest change with 135% growth occurs for airport model and the fare of 9 €/km, and the smallest growth for residential model with 13% increase with the ticket price of 3 €/km. Therefore, it could be concluded that the impact of speed is swelling by increasing travel distance and ticket price.

7.8. Processing time

Processing time as another travel time component could significantly affect the UAM travel time, particularly in shorter trips which are too sensitive to travel time. As stated by Rothfeld et al. (Rothfeld (1), Fu, Bala´c, & Antoniou, 2021), the most significant impact of reduced processing time is for short-range trips. The results of the current study illustrate that the processing time and access time have the same impact on UAM demand as both are directly determining the travel time. Similar to access time, decreasing processing time results in higher UAM demand, and the impact is increasing by raising the fare. Alike access time, the level of impact of processing time highly depends on perceived cost, which means that passengers are getting more sensitive to processing time in the higher ticket price. The increase of UAM demand resulted from halving processing time are 35%, 89%, and 239%, respectively, for (0, 3), (0, 6), and (0, 9) in airport model. And in the residential model, the impact of shorter processing time is 103%, and 22%, sequentially, for the fare scheme of (25, 0) and (0, 3).

7.9. In-Vehicle coefficient

One of the assumptions of this work is that the attractivity of this new mode of transport could overcome the travel time component in the first years of operation of UAM. Consequently, in-vehicle coefficient has been used as a representative factor for the above-mentioned assumption. However, Peksa and Bogenberger (Peksa & Bogenberger, 2020) by trying different in-vehicle coefficients varying from 0.8-1.2 have found that this attribute does not have a significant impact on the UAM performance in comparison with the fare. Taking into account two different coefficients of 1 and 0.5, it has been found, obviously, that the impact of in-vehicle coefficient is getting higher by increasing the fare similar to other time-related attributes. Alike access time and processing time, in-vehicle coefficient has direct impact on UAM travel time. Therefore, by increasing the fare for UAM, the impact of this travel-time components is increasing. Since the trips' length in airport model are considerably higher than other models, the impact of in-vehicle coefficient is relatively higher than the impact of other time-related attributes like processing time and access time. Needless to say, the change in processing time and access time is constant, 5-6 minutes, whereas the impact of in-vehicle coefficient is growing by any increase in the trips distance so as halving the in-vehicle time.

7.10. General findings

Although access time and processing time affect UAM demand similarly, access time is slightly getting more influential when the fare combinations are going to be more expensive. Moreover, access time is more significant than speed, particularly in fare combinations including distance-based fare, and for constant fare combinations more than 50 €. As mentioned earlier, in-vehicle coefficient is more influential than access time for airport passengers, and for tourists the access time is more important than in-vehicle coefficient. In addition, it is concluded that the processing time is unquestionably more significant than speed when the fare schemes including distance-based fare. In the contrary, speed is more influential that processing time for the constant fare more than 25 €. Moreover, it has been found that in-vehicle coefficient affects the UAM potential demand stronger than processing time and speed.

Goyal et al. (Goyal, et al., 2018) have reported that their respondents have been more receptive to using UAM for travel to the airport or long-distance recreational trips than for commuting. Based on the results of the current study, it could be also concluded that the main potential users of UAM which are airport passengers and tourists, and, therefore, different model variables could be ranked based on their importance and impact on the UAM potential demand. Concerning the airport model, in-vehicle coefficient is the most influential factor, following by processing time and access time which have almost same impact on the UAM demand, and speed which has the least impact in comparison with others. Similarly, tourism model follows the same ranking trend as airport model for all fare combinations including only constant fare. On the other hand, access time and processing, in-vehicle coefficient, and speed have respectively highest to lowest impact on the UAM demand in tourism model for all fare schemes containing distance-based fare.

8. Conclusion

The following sections present the general conclusions of this study, followed by a discussion about the limitations. At the end, further steps to improve the current model are also presented.

8.1. Conclusions

This research has aimed to develop a transportation model to estimate the UAM potential demand. Local and non-local travelers in Île-de-France region, France, have been targeted in this study. A transportation model in PTV VISUM traffic planning software through employing different datasets have been developed in which UAM as a new mode of transport has been integrated. The impact of different operating variables of UAM as well as different fare schemes on the potential demand attracted by different target customers have been investigated. The findings of this thesis provide promising answers to the main objectives stated in section 1.2. Generally, the main finding of this work can be summarized as follows.

- Although the number of residents' trips is considerably higher than touristic and airport trips, the majority portion of UAM trips for almost all fare combinations belongs to airport passengers, following by tourists.

- All the target groups are noticeably sensitive to number of UAM lines, and this sensitivity is even higher for constant fare schemes.

- Processing time and access time have almost the same impact on UAM potential demand, as both are contributing to travel time and having the same coefficient regarding the perceived journey time.

- Residents have shown the highest sensitivity to ticket price, so as there is no demand for different cost schemes other than (0, 3) and (25, 0). However, the demand for the mentioned fare combinations is almost negligible. Although the total number of airport trips are considerably lower than two other model, there is a demand for all the fare combination for this group of travelers because of longer trips and different mode choice behavior of airport passengers. On the other hand, tourists have had a medium behavior between two above-mentioned groups. In general, it has been found that UAM demand is more influential to distance-based fare than constant fare,

- Concerning other factors and fare combinations including distance-based fare, it has also been discovered that in-vehicle coefficient is the most influential factor, following by processing time and access time and speed for airport model. In contrast, access time and processing time, in-vehicle coefficient, and speed have respectively highest to lowest impact on the UAM demand in tourism model. This difference is due to the fact that the trips' length in airport model are considerably higher than touristic model.

8.2. Limitations

This study has however some limitations that can be summarized as follows.

- This study has investigated the potential demand for UAM. Obviously, the served demand highly depends on arriving rate of passengers at vertiports, fleet-size, etc.

- Although headway has not been found as an influential factor on potential UAM, but the UAM network capacity is directly affected by different headways.

- Due to data unavailability, some assumptions have been taken. Income level of airport passengers for which the data of similar airport has been used.

- Although for all the model the travelers have been segmented into different income categories, but it has not been precise enough to reflect the value of travel time for all potential users. For instance, business travelers with a very high level of income, yearly income more than 500,000 € even though their proportion is too small.

- As UAM is a new concept, and there is no observed data regarding mode choice behavior for this mode of transport. Therefore, the coefficient and ASC of other existing modes have been used for UAM.

8.3. Future Development

Further steps could be considered for improving the developed transportation model, particularly taking into consideration some of the above-mentioned limitations. For instance, travelers could be segmented in a more detailed manner based on level of income. Furthermore, the capacity constraint of UAM network will be implemented to find the actual number of served passengers. Last but not least, having actual demand for each UAM line known, a cost-benefit analysis will be necessary through examining different fleet-size so as to allocate the vehicles and infrastructure appropriately and to optimize the profit.

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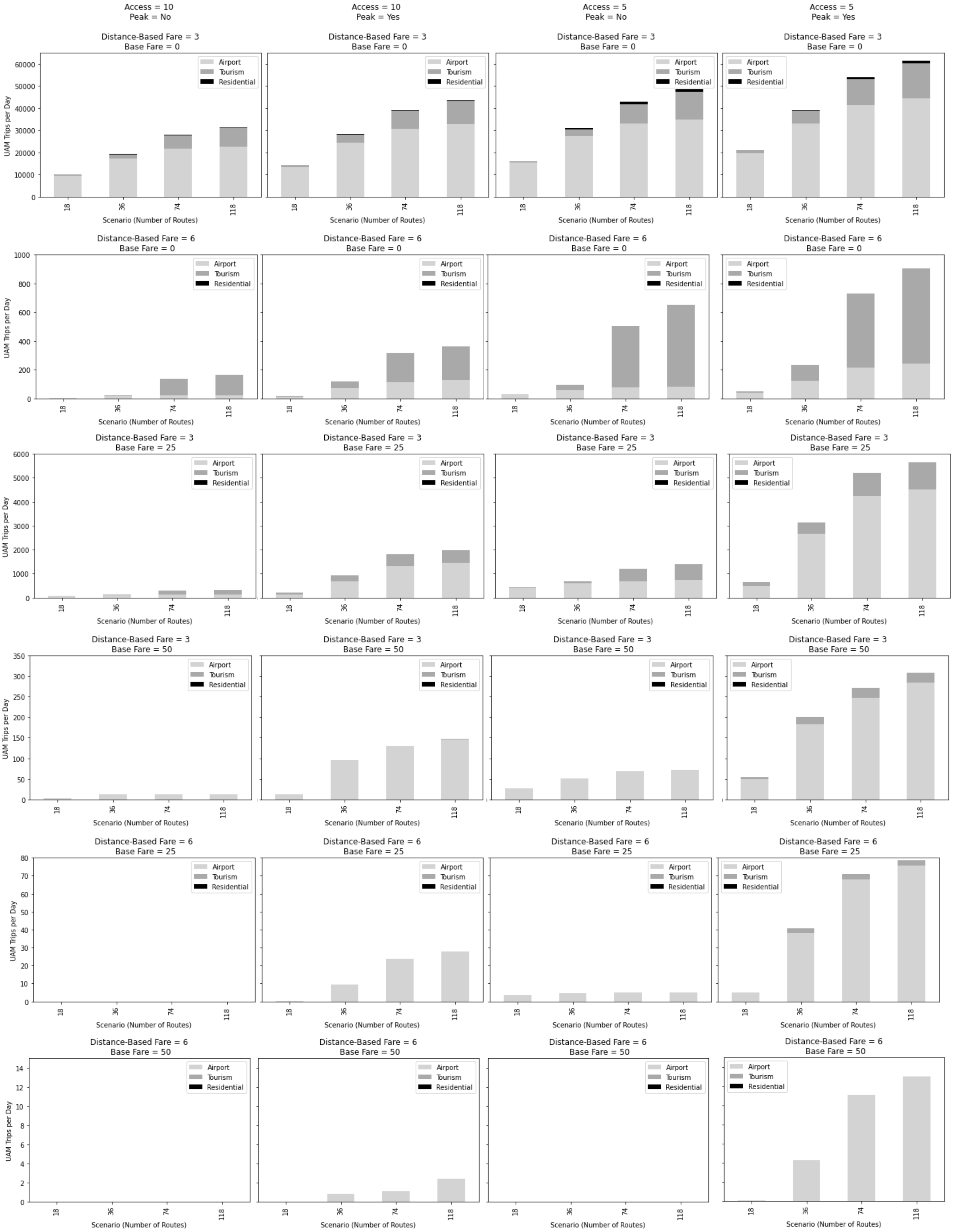
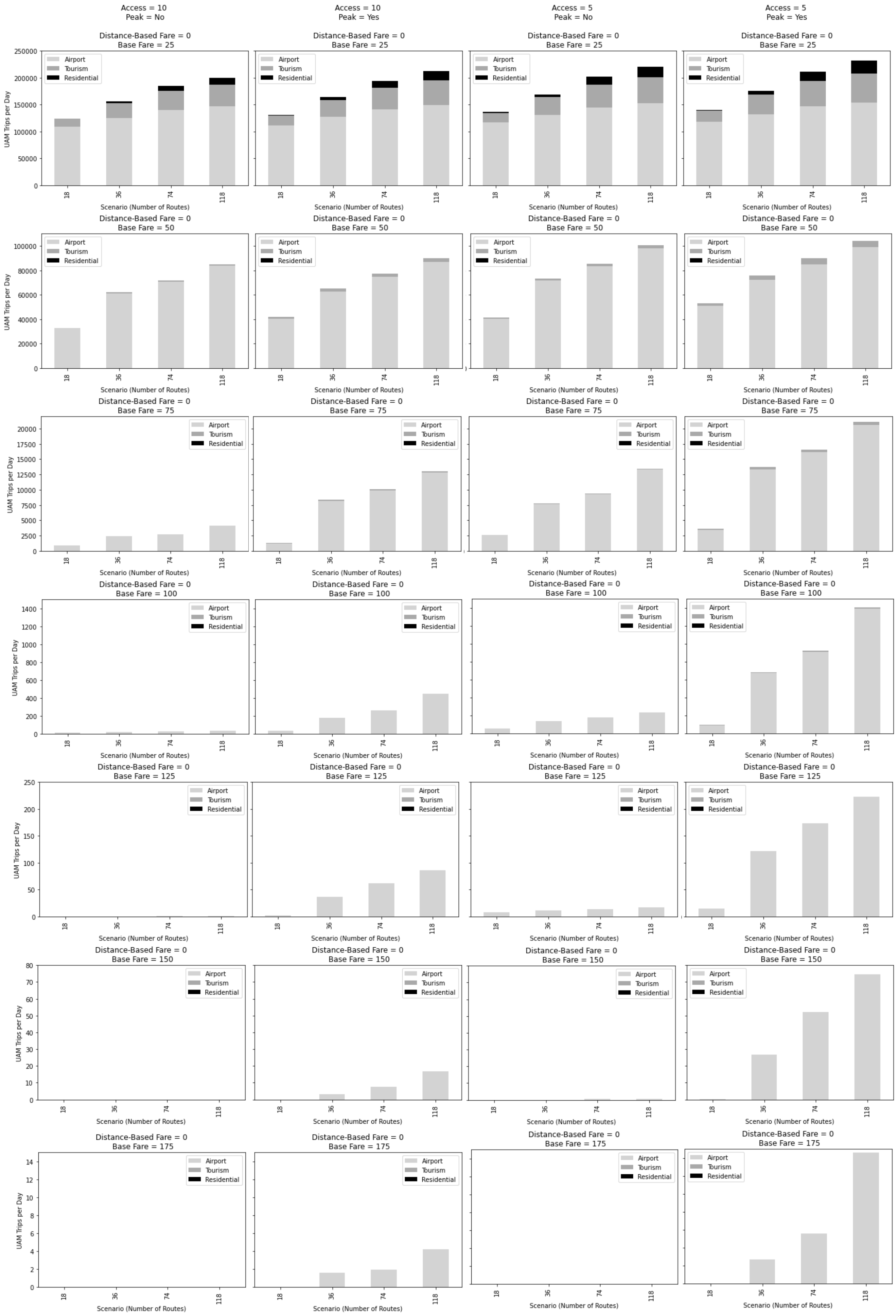
Appendix A: Access time

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Access = 10
Peak = Yes
Access = 5
Peak = No
Access = 5
Peak = Yes
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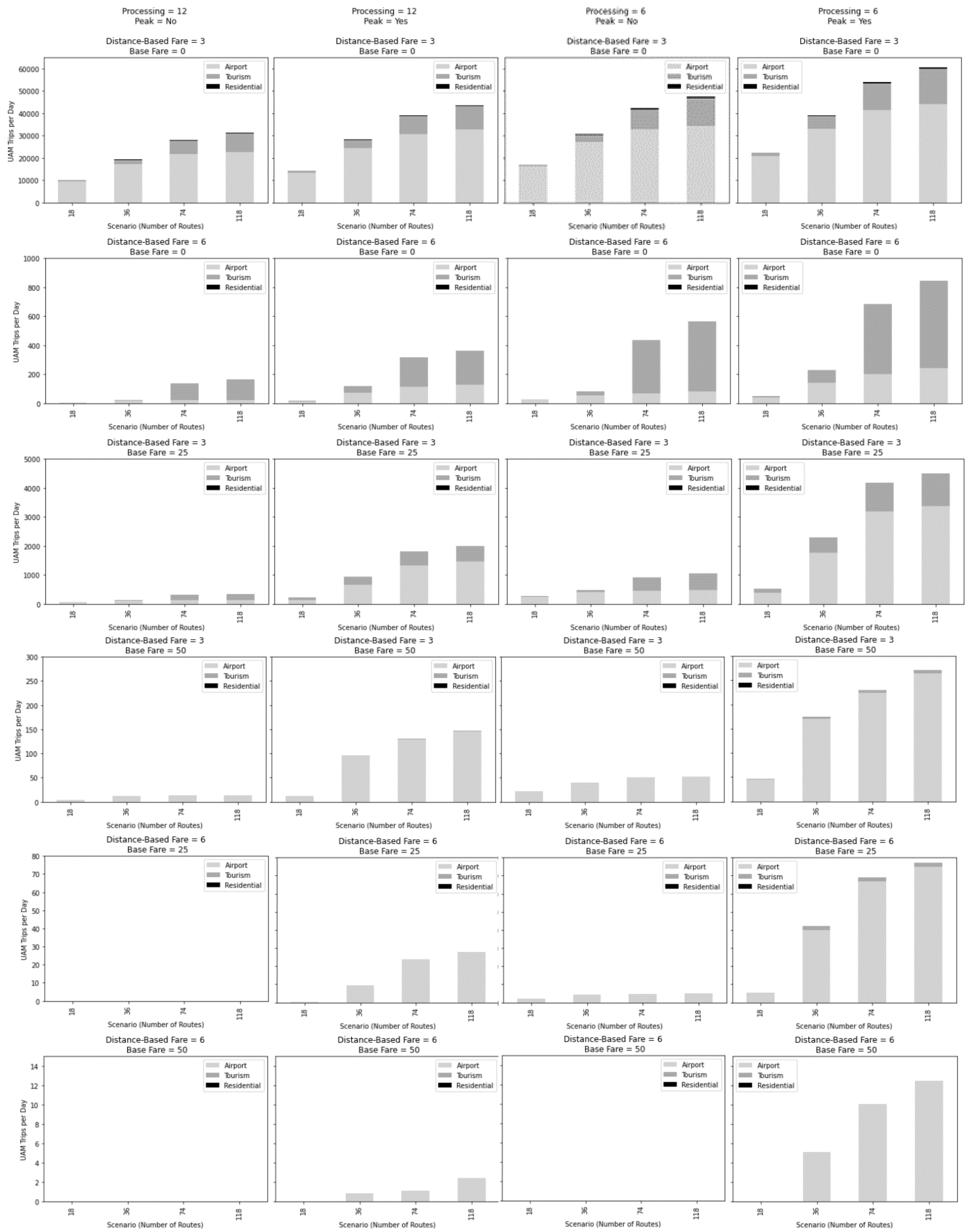
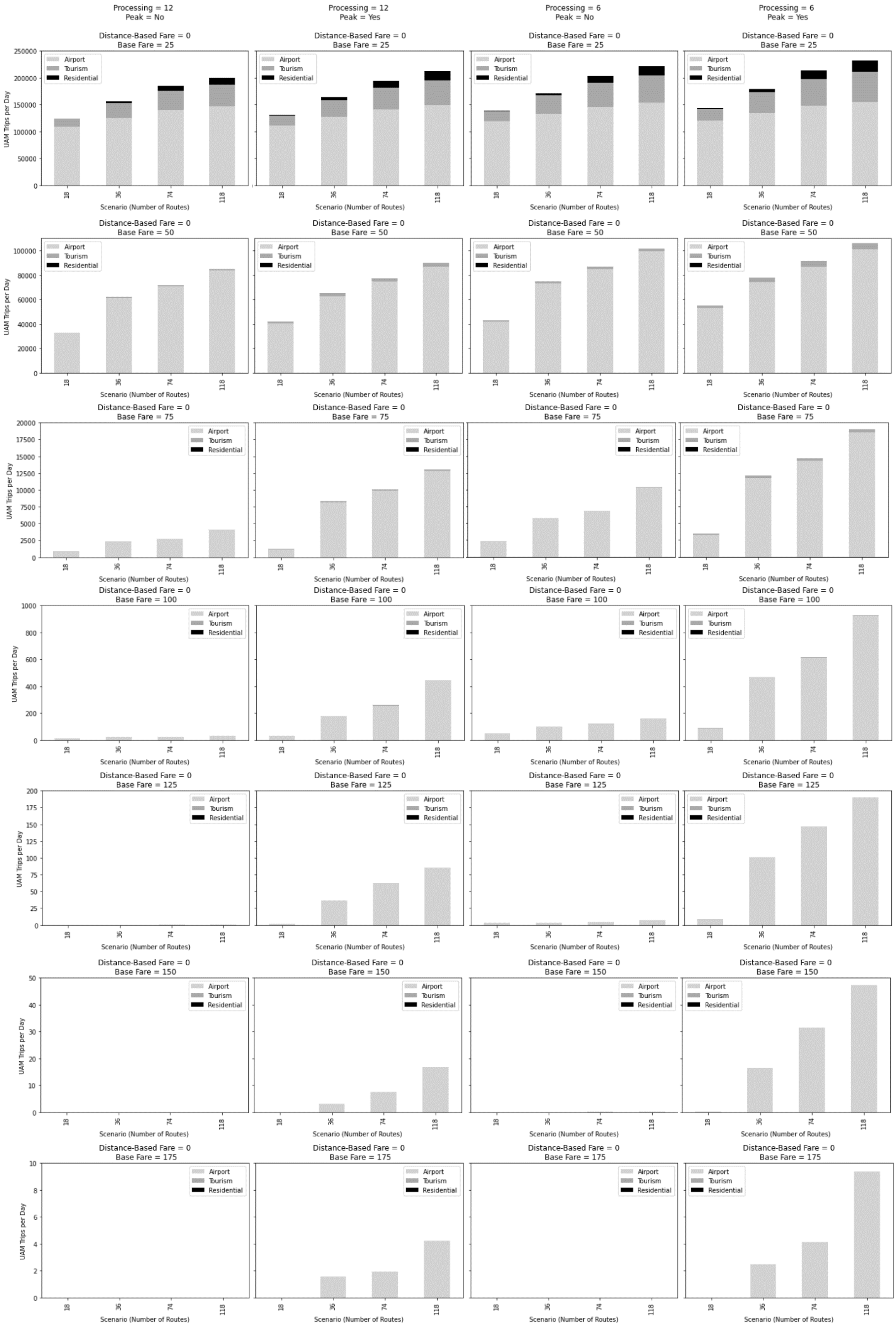
Base Fare = 25
Distance-Based Fare = 0
Base Fare = 50
Distance-Based Fare = 0
Base Fare = 75
Distance-Based Fare = 0
Base Fare = 100
Distance-Based Fare = 0
Base Fare = 125
Distance-Based Fare = 0
Base Fare = 150
Distance-Based Fare = 0
Base Fare = 175
Airport
Tourism
Residential
UAM Trips per Day
Scenario (Number of Routes)
18
36
74
118

Appendix B: Processing time

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Processing = 12
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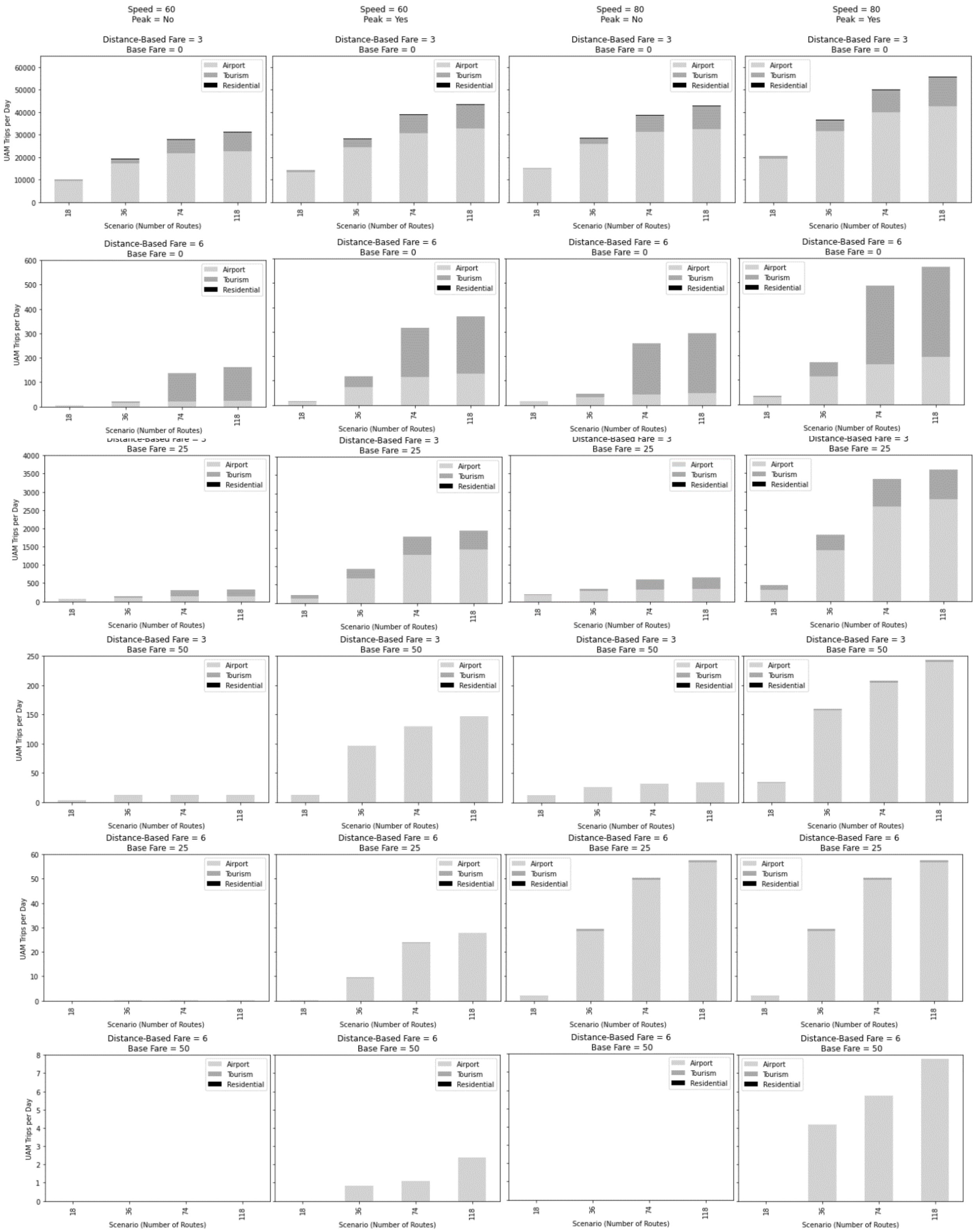
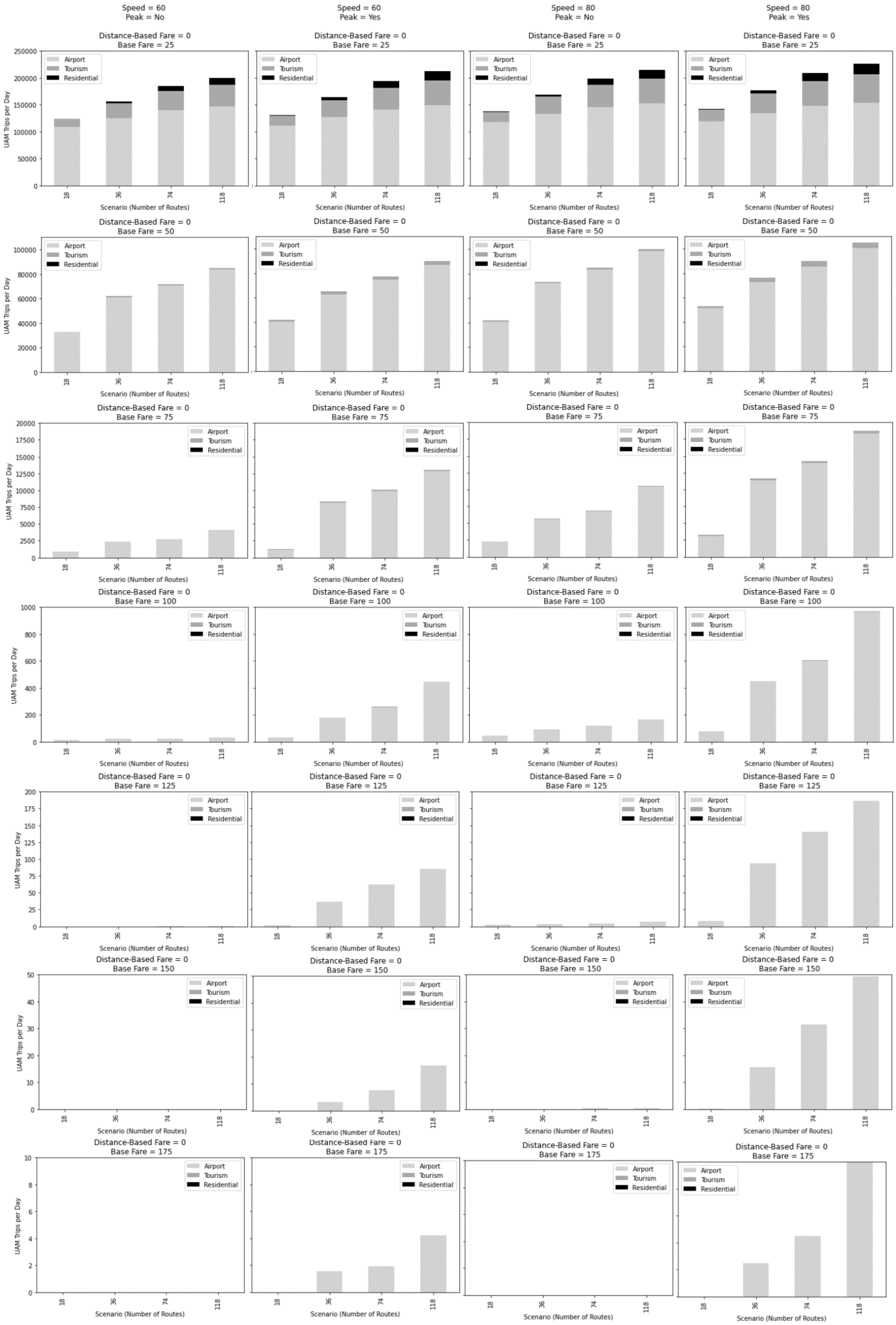
Processing = 6
Peak = No
Processing = 6
Peak = Yes
Distance-Based Fare = 0
Base Fare = 25
Base Fare = 50
Base Fare = 75
Base Fare = 100
Base Fare = 125
Base Fare = 150
Base Fare = 175
Airport
Tourism
Residential
UAM Trips per Day
Scenario (Number of Routes)
18
36
74
118

Appendix C: Speed

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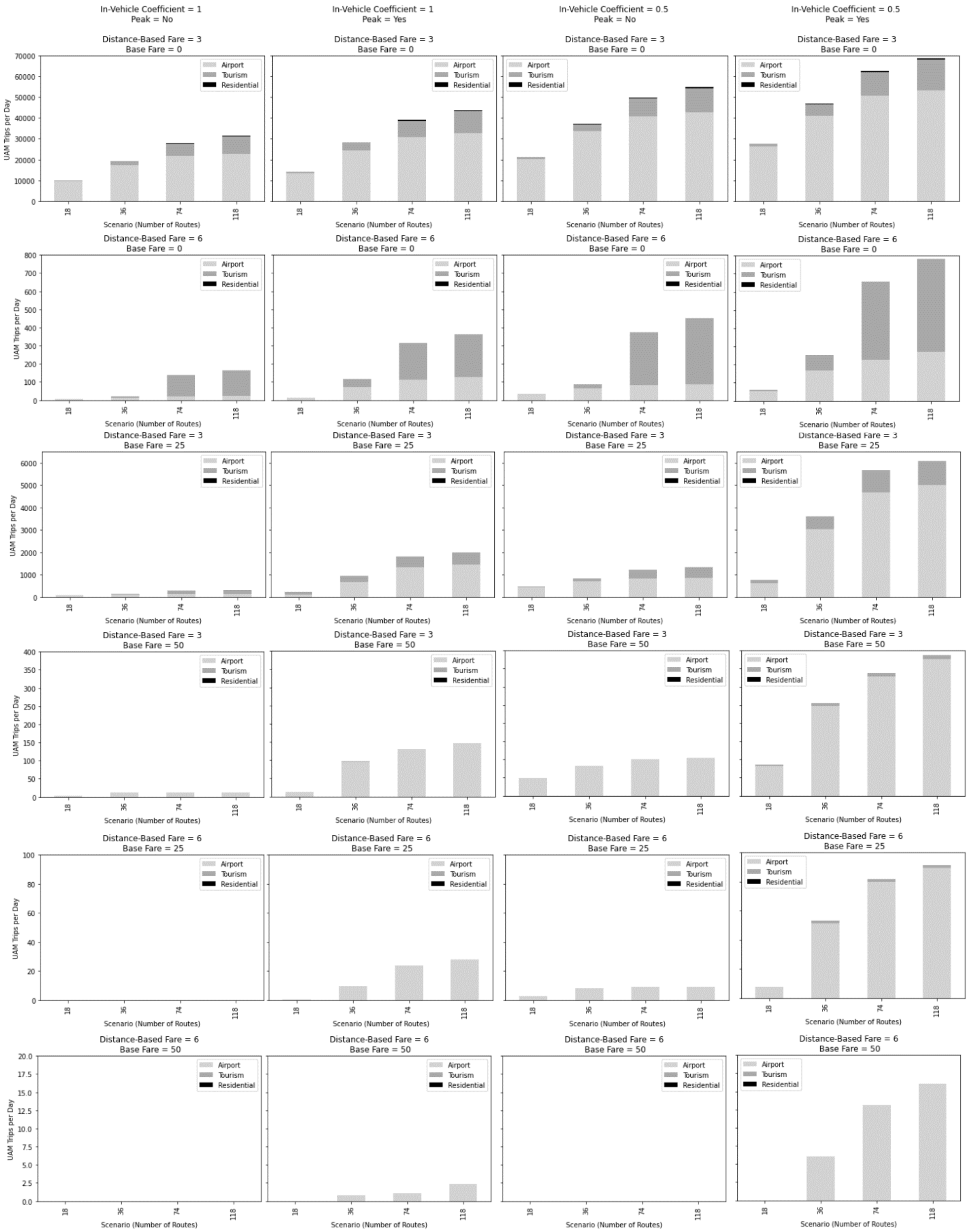
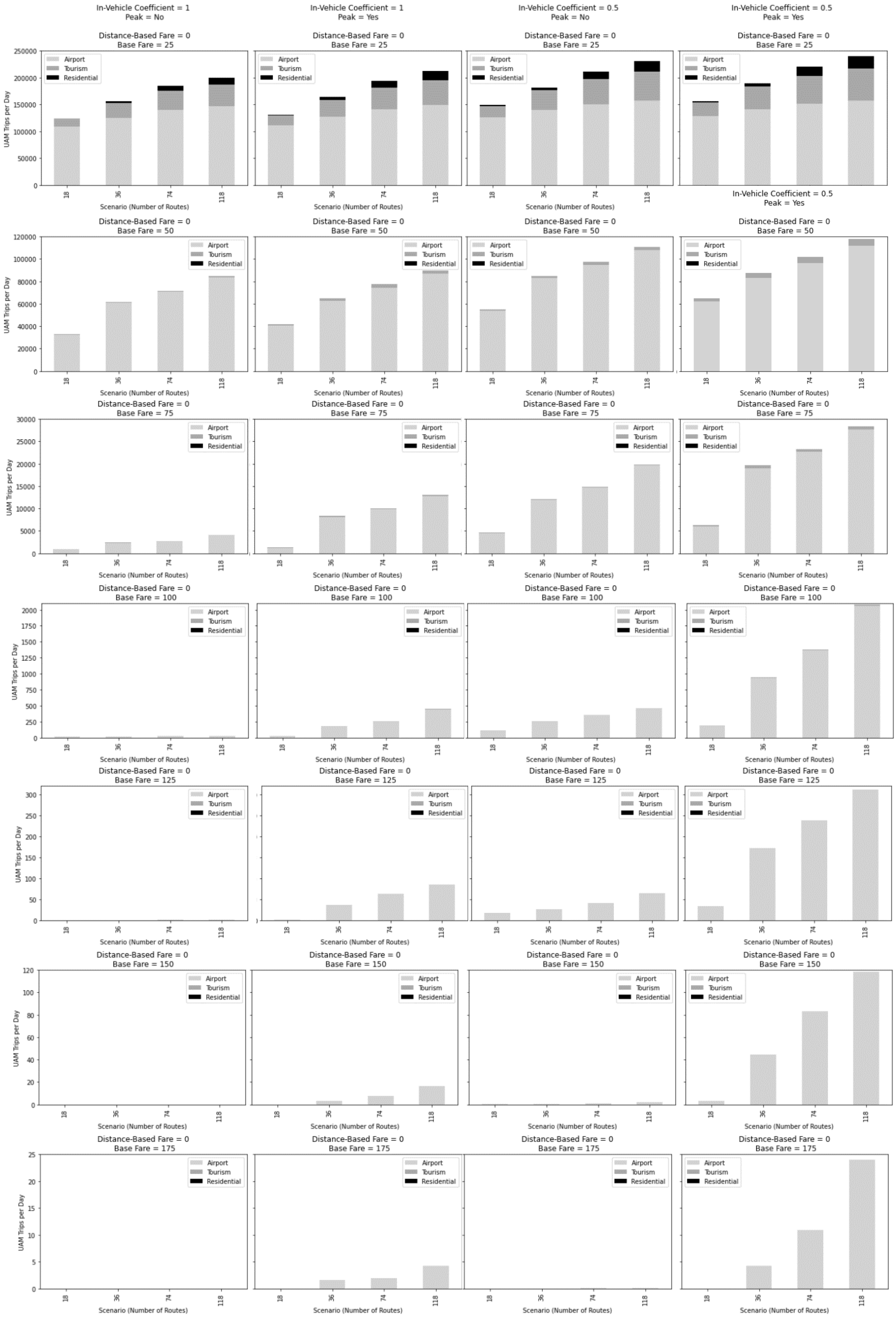
Speed = 60
Peak = Yes
Speed = 80
Peak = No
Speed = 80
Peak = Yes
Distance-Based Fare = 0
Base Fare = 25
Distance-Based Fare = 0
Base Fare = 50
Distance-Based Fare = 0
Base Fare = 75
Distance-Based Fare = 0
Base Fare = 100
Distance-Based Fare = 0
Base Fare = 125
Distance-Based Fare = 0
Base Fare = 150
Distance-Based Fare = 0
Base Fare = 175
Airport
Tourism
Residential
UAM Trips per Day
Scenario (Number of Routes)
18
36
74
118

Appendix D: In-vehicle coefficient





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Peak = No
In-Vehicle Coefficient = 1
Peak = Yes
In-Vehicle Coefficient = 0.5
Peak = No
In-Vehicle Coefficient = 0.5
Peak = Yes
Distance-Based Fare = 0
Base Fare = 25
Distance-Based Fare = 0
Base Fare = 50
Distance-Based Fare = 0
Base Fare = 75
Distance-Based Fare = 0
Base Fare = 100
Distance-Based Fare = 0
Base Fare = 125
Distance-Based Fare = 0
Base Fare = 150
Distance-Based Fare = 0
Base Fare = 175
Airport
Tourism
Residential
UAM Trips per Day
Scenario (Number of Routes)
18
36
74
118

Declaration

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

München, 22/05/2022

Hamidreza Aliar