ETHzürich

Demand estimation for aerial vehicles in urban settings

Demand estimation for Aerial Vehicles in Urban Settings

Milos Balac, Amedeo R. Vetrella, Raoul Rothfeld, and Basil Schmid

Abstract—The idea of flying has always fascinated mankind. A century ago it became reality when in 1914 the first commercial flight was offered. In recent times, many entities are planning, developing and testing aerial vehicles and systems that will move goods and people in urban scenarios. Consequently, the need to develop appropriate planning tools and to investigate the potentials for this kind of transportation is needed.

In this paper we present a methodology for simulation and demand estimation for personal aerial vehicles (PAVs) in urban settings. The methodology is then utilized to analyze the impacts of PAVs with different vehicle and system parameters on the demand. The findings show that with higher automation and falling prices, PAVs have a potential to be an important transportation mode, by serving not only mid-distance trips, but also shorter trips in urban settings. The analysis also show that unlike for car and public transport service, vehicle parameters of PAVs have a substantial impact on the demand and turnover. Furthermore, an optimization procedure that minimizes fixed costs of the PAVs by minimizing the fleet size and variable costs by minimizing the empty kilometers of PAVs for the estimated demand in the region of Zurich, Switzerland, is proposed. Optimized service ensures that much wider range of possible vehicle concepts can be utilized to serve the demand.

I. INTRODUCTION

The idea of flying has always fascinated mankind. To quote Schmitt and Gollnick [1]: "Behind the imagination of flying, which can be found in all old cultures and civilizations, there are also the basic emotional elements of mankind about freedom and mobility." On the 1st January 1914 a first commercial airline flight happened and the dream of easily and quickly reaching any part of the world transformed into reality.

At the moment of writing this paper the transportation systems have already seen the testing and in some areas of the world the introduction of autonomous ground vehicles. Commercial Unmanned Aerial Vehicles (UAVs) have also undergone testing and some were recently used to transport small sized goods. Additionally, encouraged by the fast paced technological development certain entities are already developing aerial vehicles (called Personal Aerial Vehicles - PAVs) and systems that will move people in urban settings. The opportunities and disruptive effects that this innovation in the transportation system might bring are vast and they need to be analyzed.

At the moment many countries are faced with the omnipresent congestion problems on the roads and the constant growth of traffic. In Mexico City drivers are standing on average 1 hour in congestion during peak hours, amounting

M. Balac and B. Schmid are with the Institute for Transport Planning, ETH Zurich (e-mail: milos.balac@ivt.baug.ethz.ch)
A.R. Vetrella is with the University of Naples, "Federico II"
R. Rothfeld is with the Bauhaus Luftfahrt, Germany.

to more than 8 days per year of lost time [2]. This problem could be alleviated with the introduction of the urban aerial transportation. People movement in the uncongested air space would not only reduce travel times, but will allow for less air pollution as the stop and go emissions would be eliminated. Expansion of roads would not be necessary and the gained space could be used for other purposes.

The introduction of urban commercial piloted and later fully autonomous aerial vehicles and their interaction with already existing transportation modes (both traditional and modern) in the transportation system brings many new research questions that are in need of investigation.

It is the purpose of this paper to present a methodology to investigate on a large scale the impacts of the introduction of urban aerial transportation, as well as why the exchange of the information between transportation planners and physical system developers is germane for the development and demand forecasting for this new transportation system. First estimations of the demand for urban aerial transportation services are then presented for the region of Zurich, Switzerland.

II. BACKGROUND

Traditional four-step demand models in transportation are recently being replaced by agent-based models (some examples among many can be found in [3]–[5]) since they are not suitable to forecast the demand for new transportation modes like ridesharing, carsharing, bikesharing or autonomous vehicles. As stated by Shaheen and Rodier [6] the need for models that can incorporate both land use and demographics is needed in order to properly simulate these new modes (at that time autonomous vehicles were not the topic, but fall under the same category). Moreover, the availability of these modes in both space and time needs to be considered, which the four-step approach cannot do on an appropriate level. This is obviously also true for the simulation and demand modeling of aerial vehicles in urban setting.

There are many commercial simulation tools for air traffic (SIMMOD [7], AirTop [8], RAMSrams plus [9]). Researchers have also developed air traffic simulators (e.g. see ATOMS [10], FACET [11], ELSA [12]). They all aim at representing in detail air traffic control. However, they are not able to represent people on an agent level and do not include other kinds of transportation system. This becomes a limitation when the aim is to model and analyze the demand for urban aerial transportation. The only known attempt to simulate commercial flights using an agent-based approach, where both aircraft and passengers are modeled on an agent level on all segments of the flight was by [13] using Multi-Agent

Transport Simulation (MATSim) [3]. Here MATSim was used to simulate commercial airplane flights over Europe. Aircraft are represented microscopically, while the air traffic network used was implemented at a low level of detail since the goal was not to provide an air traffic management tool. The results presented by the authors show that MATSim is able to simulate the air traffic in Europe realistically. However, simulation of urban aviation was not attempted and therefore it is the purpose of this paper to bridge this research gap.

MATSim has already been used to simulate ground autonomous vehicles in recent years [14], [15] and their impacts on the transportation system. Consequently, developing an urban aerial system as part of MATSim is a natural next step.

Previously research has already been undertaken to investigate how Unmanned Aerial Systems could impact the operations at airports [16]. The authors explain that with the fast paced technological developments this is not a far distant future. On the other hand, at the moment of writing this paper several entities are planning to commence operation of urban aerial transportation services with different characteristics. Airbus is currently developing a Passenger Unmanned Aerial Vehicles (PUAV) capable of transporting people in the urban area [17]. Amazon has already performed a packet delivery using a drone in December 2016 [18]. Swiss Post has also tested drone delivery in Lugano, Switzerland in 2017 [19]. Uber has made plans to install aerial taxi service in Dallas and Dubai [20]. In Dubai, the government officials are highly motivated to have PAVs moving people within the city boundaries in the next couple of years. In [16] the prospects of autonomous flying at the airports is also envisioned in the future. All these plans and ideas are a signal that proper planning and research on this topic is urgently needed.

This is why, taking into account the interest of industry to create an aerial transportation system, it is necessary to analyze the performance of these vehicles and design a proper transportation system that is able to integrate the aerial mode with more traditional modes.

An additional challenge in modeling PAVs is the variation in current PAV concept designs. While the idea of a flying car–with whom PAVs are often being compared–has been around nearly as long as the first successful flight it is now that personal air transport seems technologically and economically viable. Based on advances in battery technology, electric propulsion and regulatory frameworks, PAV concepts, intended for intra-urban regional passenger missions, are being developed and examined by a multitude of corporate as well as start-up companies. The industry interest stems from various branches as can be observed by the diversity of involved companies such as Airbus, NASA and Uber ([21]).

One advance in particular, the advance of electric propulsion, provides novel and–so far–unattainable freedoms in designing the air vehicle's system architecture, as it facilitates the use of distributed propulsion. Distributed electric propulsion is expected to allow for the development of relatively quiet, near emission-free and highly reliable PAVs–all of which are preconditions for intra-urban air travel–and provides the basis for unconventional air vehicle designs. Thus, current PAV concepts vary greatly in morphology, passenger capacity, and

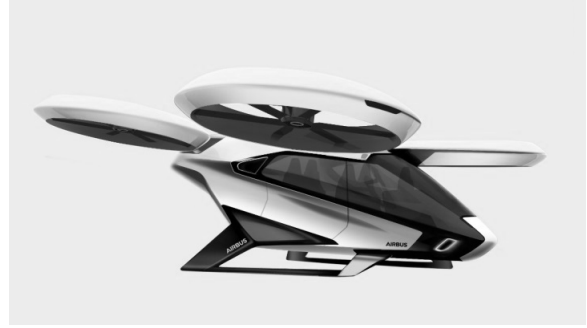expected performance.

Fig. 1. Rotor-based lift-production during cruise ©Airbus.
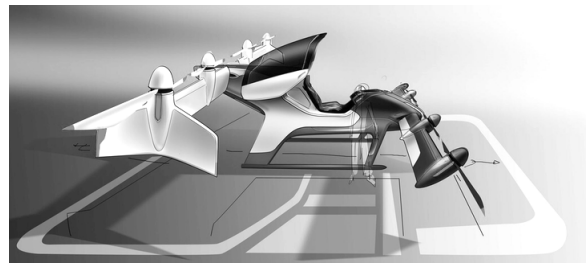

Fig. 2. Fixed-wing lift-production during cruise ©Airbus.

While there are grave morphological distinctions between various PAV concepts, e.g. rotor-based and fixed-wing lift-production during cruise (see Figures 1 and 2 for respective examples), it is the concepts' passenger capacity and performance in speed and range that is of principal interest for modeling the integration of PAVs into a transport system.

Figure 3 shows the disparity across PAV concepts by plotting the expected range, cruise speed, passenger capacity and energy supply of an excerpt of known PAV concepts. According to [21] current PAV concepts are intended to be supplied with energy by electric (56%), fuel-based (23%), hybrid-electric (9%), and other (e.g. hydrogen) (12%) means. The type of energy supply greatly influences the vehicle's performance data, with the ranges of electric concepts laying between 27 and 370 km with 167 km on average (SD 136 km), while fuel-based concepts range from 112 to 1,200 km with an average of 708 km (SD 324 km). Interestingly, between the three hybrid-electric concepts, of which range expectations have been published, the range varies between 800 and 2030 km (AVG 1210 km, SD 710 km)–surpassing fuel-based concepts. One hydrogen-based concept, the only remaining concept with published range expectation, has an expected range of 500 km.

For speed, Shamiyeh et al. [21] lists electric concepts which vary between 70 and 322 km/h (AVG 198 km/h, SD 88 km/h), while fuel-based concepts are expected to achieve 211 km/h on average–starting from 112 km/h and up to 457 km/h (SD 106 km/h). Again, the hybrid-electric concepts are expected to surpass the fuel-based concepts with speeds between 320 and 630 km/h (AVG 427 km/h, SD 176 km/h). Other concepts (3) range from 100 to 250 km/h (AVG 200 km/h, SD 87 km/h).
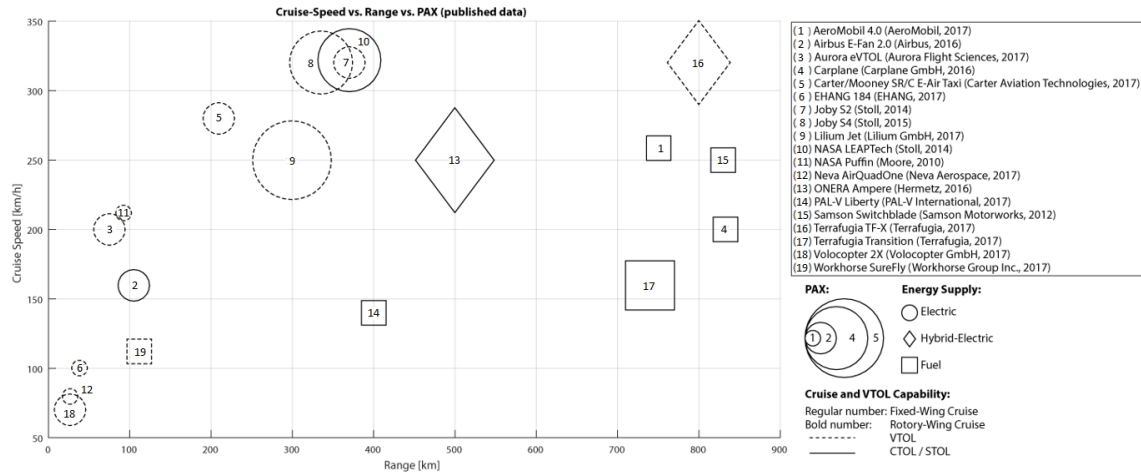
Fig. 3. Comparison of different PAV concepts (adapted from [21]).

Finally, the concepts also vary in their designed passenger carrying capacity, where–across all types–the PAV concepts vary in their capacity between one and six passengers, with most concepts being designed as one- (28%) and two-seaters (40%). The hybrid-electric concepts are expected to seat the most passenger (N 4, AVG 4.50, SD 1.91), while electric (N 24, AVG 2.25, SD 1.33) and fuel-based (N 10, AVG 2.20, SD 1.03) concepts–the majority of concepts–are planned with fewer seats.

PAVs are novel concepts, whose design mission and architecture are not yet clearly defined, as can be derived from the broad ranges in expected concept ranges, speeds and passenger capacities. While most PAV concepts are designed for short-haul missions with one or two passengers, others more closely resemble existing regional aircraft with medium-haul ranges and passenger capacities. Which concepts are best-suited for any given urban region will have to be determined based on that region's transport demand and circumstances.

Taking all this into account, close collaboration is needed between different stakeholders and research fields in order to obtain viable solutions for the integration of and demand forecasting for aerial urban systems in the transportation networks. Transport planners need to have a close exchange of information with aerial vehicles developers in order to properly plan, develop and forecast the usage of aerial systems. Therefore, it is the purpose of this paper to propose a methodology for the estimation of demand for the urban aerial transportation. Subsequently, the proposed methodology is used to provide first insights on the impacts of different technologies currently in development on the demand for PAVs.

III. METHODOLOGY

A. Demand Modeling

Modeling and forecasting the demand for PAVs is challenging. Careful planning and exchange of information between aerial vehicle developers and transport planners is essential in the early stages of research in order to realistically forecast the demand for this novel transportation mode. As was already explained in [22] research on the aerial network design, where topography, population densities, no-fly zones, weather conditions are taken into account, aerial vehicle technology development and demand modeling for this kind of systems, and their interaction is of utmost importance.

With all this in mind and since four-step models are not suitable to model this kind of transportation mode we advocate to use an agent-based model which can represent each player in this complex system on an agent level and which can represent both land use and socio-demographics. We propose to use a multi-agent transport simulation (MATSim).

MATSim through its use of the agent paradigm [23] simulates daily life of individuals. Each agent in MATSim has a daily plan of trips and activities, such as going to work, school, leisure or shopping. The initial daily plans of agents are provided in the initial demand together with supply models, e.g. street network, building facilities and public transport schedules. The plans of all agents are executed by a micro-simulation, resulting in traffic flow along network links, which can cause traffic congestion. After the micro-simulation some of the agents are allowed to re-plan their daily schedule in order to increase their utility. This process is then repeated until the equilibrium is achieved.

In this study agents are allowed to perform mode and route choice. Mode choice is performed using a novel approach first presented and tested in [24]. In this approach a specific mode choice model is implemented as compared to the previous approach in MATSim where agents were randomly trying out modes in order to increase their utility [3]. Pairing a mode choice model with an agent-based simulation like MATSim provides not only a more accurate way to predict agent's choices, but also reduces the computation time by reducing the amount of micro-simulations needed to reach the equilibrium state.

The mode choice model developed in this study is based on the national travel diaries and a stated preference survey performed in connection with the national travel diaries survey [25]. Parameters of this Multi-nominal logit (MNL) model can be seen in Table I. Since, naturally PAVs were not part of these

Mode	Variable	Parameter	robust-t test
Walking	Constant	1.1275	8.64
	Travel time [min]	-0.0670	-6.44
Cycling	Constant	0.4809	5.03
	Travel time [min]	-0.0617	-9.9
Car	Travel time [min]	-0.0409	-12.48
Public Transport	Constant	-0.4671	-6.44
	Travel time [min]	-0.0364	-13.14
	Access time [min]	-0.02084	-5.03
Cost	[chf]	-0.1045	-11.24
Number of decision makers:			4961
Number of observations:			40070
LL(null):			-37867.35
LL(final):			-27067.07
Rho2:			0.2852136
Estimated parameters:			12

surveys as currently they do not exist in practice, we have assumed the value of travel time for this mode to be similar to public transport. The approximation can be justified looking at the literature on the value of travel time for automated vehicles as discussed in the Discussion section of this paper. The utilities of each alternative in this model are computed using linear utility function:

$$U_{i,j} = \alpha + \beta_{cost} \cdot cost + \beta_{i,traveltime} \cdot t_{travel}$$
$$+ \beta_{i,accesstime} \cdot t_{access} \qquad (1)$$

for mode i and trip j. For all modes except public transport and PAV access time is assumed to be 0.

B. Simulation and costs of different transportation modes

The modes available to the agents are car, public transport, cycling, walking and PAV. Driving a car is physically simulated on the network, where agents interact with each other, thus creating congestion. Public transport routing is done via R^5 routing platform [26], but the vehicles were not physically simulated on the network. In this case as well as for cycling and walking, the agents were teleported between their origin and destination based on the estimated travel time. In case of PAV, agents have to walk for certain time to reach a PAV and then their travel time to the destination was estimated as:

$$t = 2 \cdot t_{liftoff} + d/v_{cruising} \qquad (2)$$

where $t_{liftoff}$ is the liftoff time, d is distance traveled and $v_{cruising}$ is the cruising speed. Both walking and flying to the destination is executed using teleportation. Considering the level of demand for PAVs at the moment this is a reasonable simplification since the level of interaction would be very low between different PAVs.

Each agent in the simulation contains personal information on the driving license, car and season ticket (for public transportation) ownership. This information is used in the mode choice model to first define which modes an agent can use and second to calculate the costs of a given trip for car and public transport trips. The minimum cost of driving a car is set to 1CHF and then 0.176CHF for every kilometer. For public transport, those that do not own a season ticket

have to pay a minimum price of 2.6CHF (which is the price of a short distance ticket in the city of Zurich). If the agent holds a GA (nation wide season ticket) it will pay 0.1CHF/km, 0.18CHF/km if it has a HT (nation wide half fare card) and otherwise 0.36CHF/km. For short distance trips (less than 5km) if the agent holds a regional season ticket, it will cost him 0.1CHF/km to make a trip with public transportation.

IV. RESULTS

The simulations were carried out using a Zurich scenario which covers the area of 30km radius circle around the Zurich city center. It is a very convenient place to perform the study because of several advantages. First, the scenario is well tested and previously used in many studies, second it allows not only intra- but also inter-city travel and lastly it provides many possible use cases for aerial transportation, i.e. travel over hilly regions, rivers, lakes and other natural obstacles that can limit the ground transportation performance.

In order to reduce computational burden the population of the area is scaled down to 10%, which means that the size of the simulated population was approximately 160,000. Accordingly, the network capacities are adjusted in order to take into account the scaled number of vehicles on the roads. The synthetic population used in the simulation is a representative of the population living in and commuting to the study area [27].

PAV vehicle parameters used in this study are: cruising speed (20m/s, 25m/s, 30m/s), liftoff time (60sec, 120sec, 180sec) and access time (120sec, 300sec, 600sec). These assumptions are based on the current technological parameters found in the literature as explained previously. Different access times should be seen as the average access times to the closest landing platform of PAVs for a given scenario. Even though at the moment landing stations are not explicitly modeled, this can be considered as an approximation.

Pricing assumed is inspired by the current Uber Black prices for Zurich, Switzerland: 4CHF/km plus a base fare of 4CHF. The assumption comes from the Uber announcements of their plans for piloted PAVs. Moreover, as Uber officials have recently presented [20], they expect that the costs for aerial transportation in the urban areas with full automation

will fall below the costs for car ownership. In order to test how the increase of the automation would impact the demand, scenarios with half of the initial per kilometer price are also simulated .

Spatial distribution of PAV trips for the scenario with parameters - 30m/s, 60sec liftoff time, 120sec access time, can be seen in Figure 4. The ability to travel in a straight line and not having to stay on the congested roads, clearly benefits long distance commuters. Most of the trips are over the Zurich lake, mountain ranges and in areas with not so good public transport connection.

Figure 5a shows the amount of trips served with PAVs. Increasing liftoff and access time both have negative effect on the amount of served trips, which is expected. However, what is important is that the liftoff time has a higher negative effect than the access time. Interestingly, higher the speed the lower the average distance traveled (Figure 5b). This means that with higher speeds people are more likely to chose the PAV for shorter distance trips, since it is more likely to overcome the initial burden of having to take a PAV. Increasing the access time is also increasing the average trip distance, meaning that short distance trips are no longer desirable, which makes sense.

The turnover for each combination of the tested parameters can be seen in Figure 6b. Decreasing speed, increasing liftoff and access time all have negative effects on the turnover. However, this does not necessarily mean lower profit as this depends on the cost of the vehicle production, maintenance and so on. Comparing the systems I (with 20m/s, 120sec liftoff and 300s access time) and II (30m/s, 180s liftoff and 300s access time) it can be observed that system II can serve almost the same number of trips as system I. Additionally, the turnover is very similar, so the actual financial benefit of having faster aerial vehicles is lost with an increase of liftoff time. Unlike for car and public transport services, where speed of vehicles is constrained by the infrastructure and regulations and not so much by the vehicle parameters, the demand and performance of PAVs is substantially affected by the utilized PAV concept. Therefore, all these parameters need to be considered when making an implementation decision for this kind of a system.

With a 50% reduction in the per kilometer price for PAV trips a substantial increase in the amount of trips (Figure 7a) can be observed. Having lower prices the agents are starting to take the advantage of much faster travel speed also for short distance trips as the lower price overcomes the burden of walking to the aerial vehicles. This effect can be seen in the reduction of average distance in Figure 7b. This however comes at a price, many short distance trips means a higher requirement for communication between vehicles, organization of the routes, more landing platforms etc.. Having almost 18,000 (scaled up to the full population of the Zurich area) take offs (Scenario with 30m/s, 120sec access time, 60sec liftoff time) and landings per day on the area of this size would require considerable planning. This number must be considered as an uper bound since aspects that are not currently considered in our simulations can and will influence accessibility, speed and routes of this kind of service. This is discussed in detail in the next section.

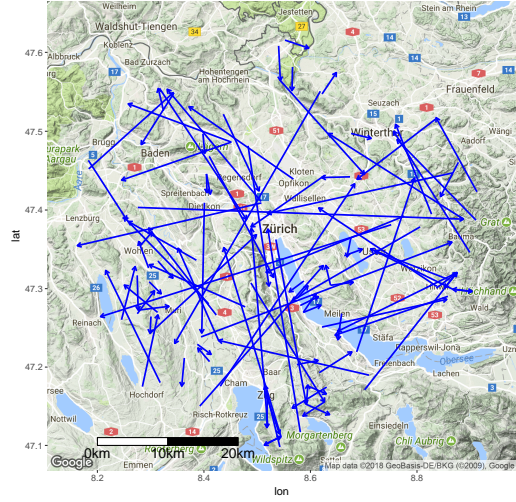The turnover increases between 2 and 5 times for different

Fig. 4. Spatial distribution of PAV trips for the scenario with 30m/s crusing speed, 60s lift-off time and 120s access time and normal pricing.

PAV systems with the decrease of the price (Figure 8b). However, the increase in the amount of added infrastructure, fleet size, maintenance, might overcome this increase in turnover, so each system operator would need to find a proper balance.

A. Optimization of the service

Using the results obtained from the simulation on the potential demand for the PAV service we can estimate the minimum number of vehicles needed to serve all PAV trips. The demand contains all the information on PAV trips, their origins, destination, departure time and arrival time.

Lets assume we have a total of N passenger trips with PAVs. We form a directed graph G = (V,E) where each start $(v_{i,s})$ and end $(v_{i,e})$ point of a PAV trip is a vertex (see also Figure 9 for a simple example). We define $t_{i,s}$ as a time when the PAV departs from the vertex $v_{i,s}$ ($i \in 1, .., N$) and $t_{j,e}$ as a time when the PAV arrives at the vertex $v_{j,e}$ ($j \in 1, .., N$) with the passenger during the simulation.

Edges of this graph are connections between start and end point of a single PAV trip and also connections between each arrival $(v_{i,e})$ and departure (v_i, s) vertex. However, because of time and speed constraints vehicle cannot reach every departure point after arrival at a specific vertex. Therefore, edges between a pair of vertices that either equation 3 or 4 hold, were removed from the graph .

$$\forall t_{i,s} < t_{j,e} \tag{3}$$

$$\frac{d(v_{i,e}, v_{j,s})}{v_{cruising}} + 2 \cdot t_{liftoff} > (t_{j,s} - t_{i,e}) \tag{4}$$

where function $d(v, u)$ calculates the crow-fly distance between two vertices based on their location in space. $v_{cruising}$ is the cruising speed of the vehicle and $t_{liftoff}$ is the time required to liftoff and land. In the example shown in Figure 9 vertices $v_{2,e}$ and $v_{1,s}$ are not connected because of criteria in equation 3 and vertices $v_{1,e}$ and $v_{2,s}$ are not connected because
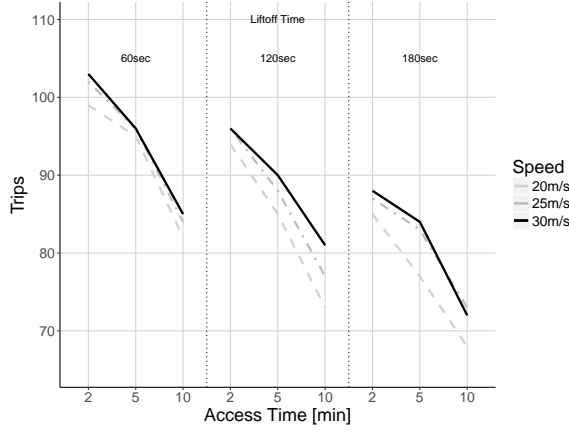
(a) Trips
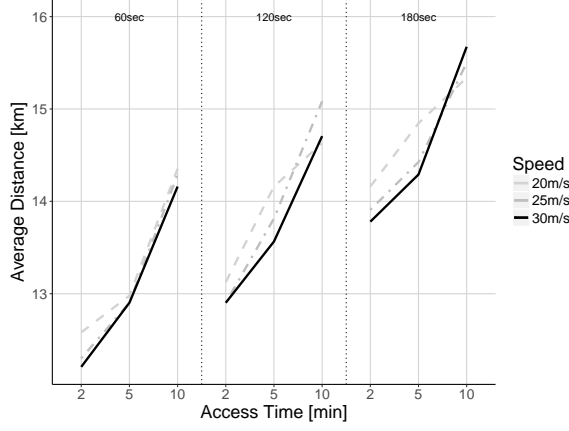
(b) Average Distance

Fig. 5. Simulation results for the normal pricing structure (a) amount of trips served with the PAV system (b) average distance of the PAV trips.

(a) Travel time

(b) Turnover

Fig. 6. Simulation results for the normal pricing structure (a) average travel time of PAV trips (b) Turnover of al PAV trips.

the vehicle cannot reach vertex $v_{2,s}$ in time because of the criteria in equation 4. The v_{source} is vertex that is connected to all stating points of PAV trips with a passenger and v_{sink} is a vertex that is connected to all end points of PAV trips with a passenger.

The objective function is represented using equation 5. $c_{i,j}$ represents the amount of vehicles moving over the edge $e_{i,j}$ and is equal to either 0 or 1 (equation 8). Flow conservation constraints (equations 6 and 7) show that the amount of vehicles reaching vertices $v_{i,s}$ and leaving vertices $v_{i,e}$ needs to be equal to 1.
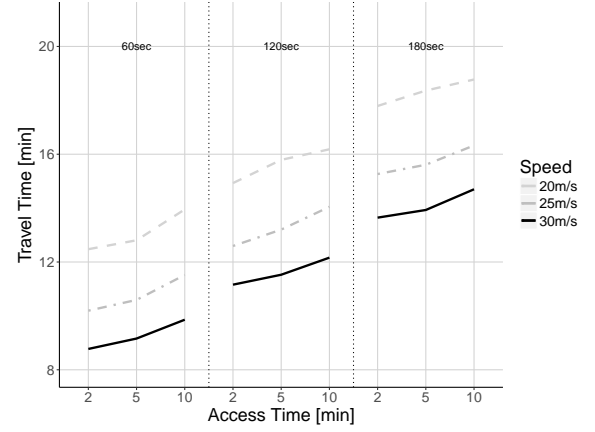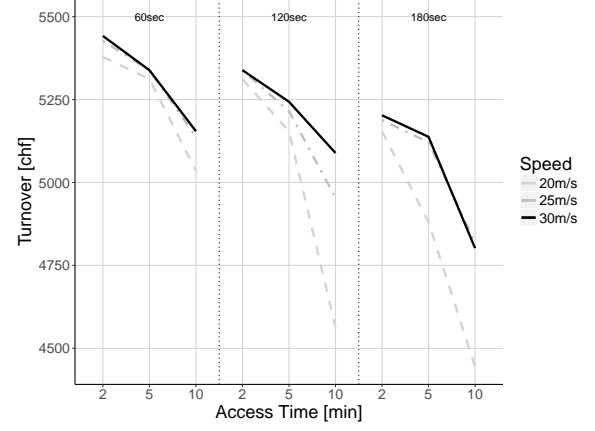
$$\text{Min} \sum_i c_{i,sink} \tag{5}$$

Subject to:

$$\sum_k c_{k,i} = 1 \quad \forall i \in \{1,..N\} \tag{6}$$

$$\sum_l c_{i,l} = 1 \quad \forall i \in \{1,..N\} \tag{7}$$

$$c_{i,j} \in \{0,1\} \tag{8}$$

This problem is an example of a minimum cost network flow problem. It was solved using a Gurobi optimizer.
Two most interesting cases to analyze are the ones with the most PAV trips for two different price structures, that is with the 30m/s cruising speed, 60 seconds liftoff time and 120 seconds access time. The minimum amount of required vehicles for the case of normal pricing is 10 for 103 trips and 53 for 1,824 trips for the reduced pricing scenario. As the amount of trips grows the ratio between the required fleet size and the amount of served trips drops. Distances covered by vehicles in these two scenarios can be seen in Figure 10. The high covered distances show that depending on the range of the PAVs used by the operator it might be necessary to increase the fleet size in order to be able to satisfy the demand.

The average mileage of PAVs is quite high when we consider the average PAV trip distance from Figures 5b and 7b. The reason is the empty mileage of PAVs which are around 65% of the time traveling without a passenger in order to reach the next pick up location. This is undesirable and unprofitable. Therefore, another optimization is required to minimize the total distance of all PAVs in the system in order to minimize variable costs. The directed graph G=(V,E) is formed in the same way as in the previous optimization procedure using the constraints in equations 3 and 4.
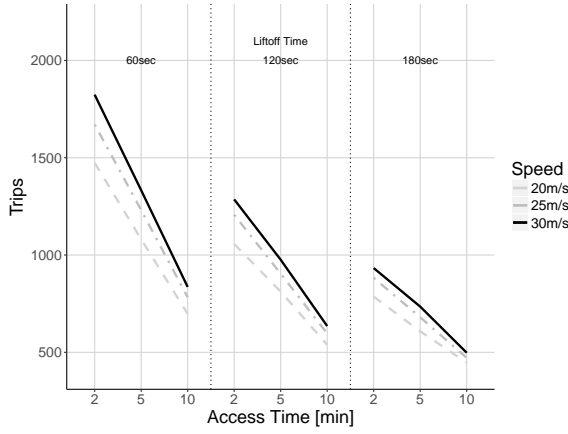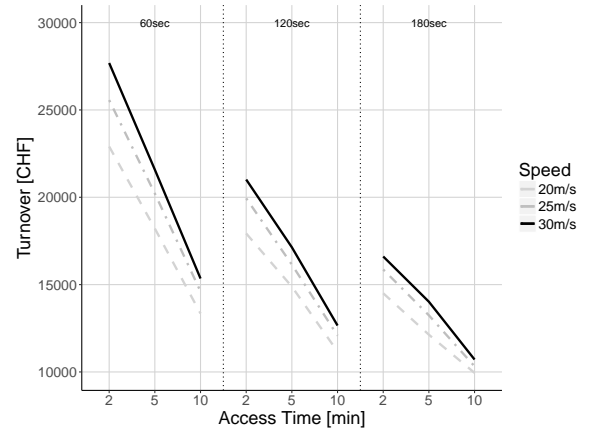
(a) Trips
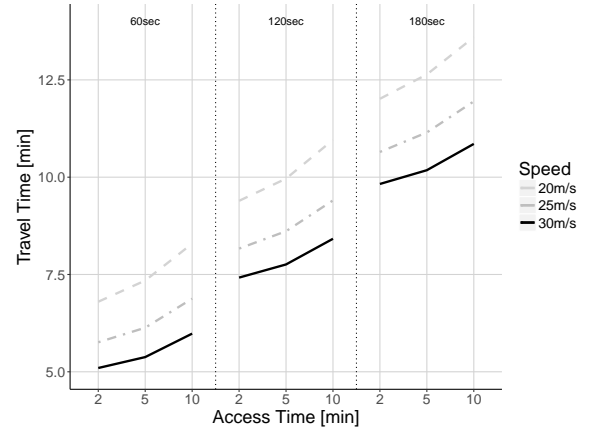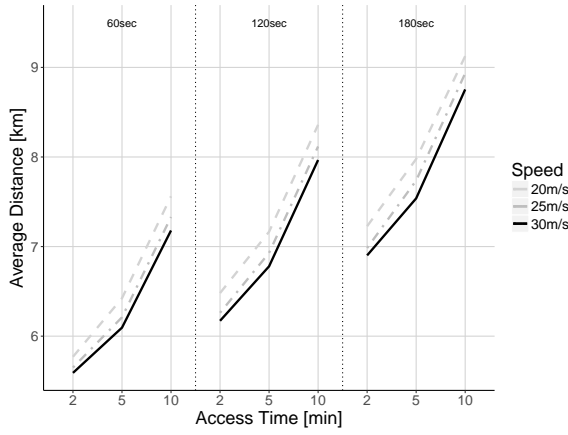
(b) Average Distance

Fig. 7. Simulation results for the reduced pricing structure (a) amount of trips served with the PAV system (b) average distance of the PAV trips.

(a) Traveltime

(b) Turnover

Fig. 8. Simulation results for the reduced pricing structure (a) average travel time of PAV trips (b) Turnover of al PAV trips.

The objective function for this optimization problem is shown in equation 9. $d_{i,j}$ represents the distance between vertices $v_{i,e}$ and $v_{j,s}$. Equation 12 represents the constraint that the number of vehicles leaving the system has to be W which was obtained from the previous optimization procedure.

$$\text{Min} \sum_{i,j} c_{i,j} \cdot d_{i,j} \tag{9}$$

Subject to:

$$\sum_{k} c_{k,i} = 1 \quad \forall i \in \{1, ..N\} \tag{10}$$

$$\sum_{l} c_{i,l} = 1 \quad \forall i \in \{1, ..N\} \tag{11}$$

$$\sum_{i} c_{i,sink} = W \tag{12}$$

$$c_{i,j} \in \{0, 1\} \tag{13}$$

Figures 11 and 12 show the total and passenger mileage per PAV for these two scenarios. A substantial reduction in the mileage is achieved by optimizing the empty flying distance. In this way both fixed and variable costs for the operator
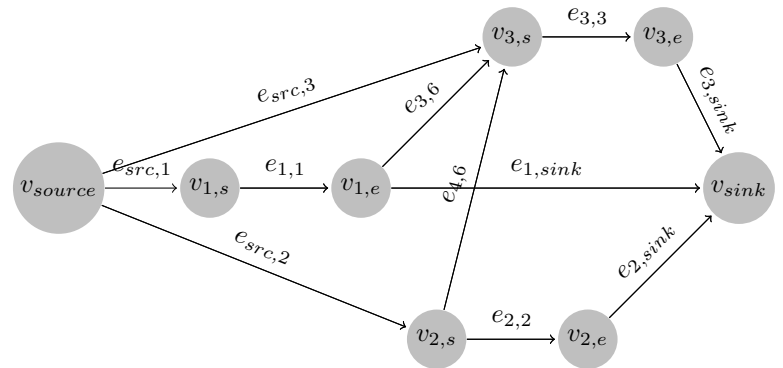

Fig. 9. An example of a graph G=(V,E) with 3 PAV trips.

are minimized given the demand. Moreover, with average distances below 400km per PAV a wider range of possible PAV technologies can be utilized to serve the demand estimated for the Zurich region.

V. DISCUSSION

The results presented in the previous section show that PAVs capabilities and their accessibility will have substantial effects on the demand. More importantly, lowering the price from the
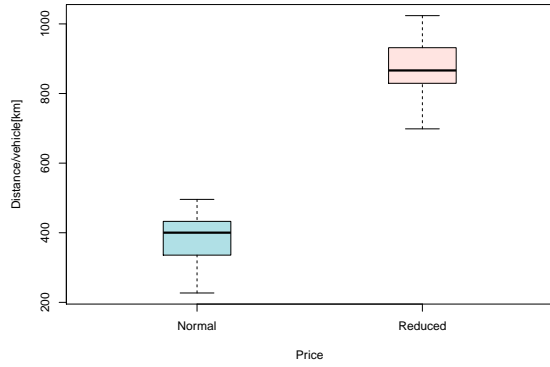
Fig. 10. Daily distances covered for the scenarios with 30m/s speed, 60sec liftoff time and 120sec access time, with the minimized number of vehicles.
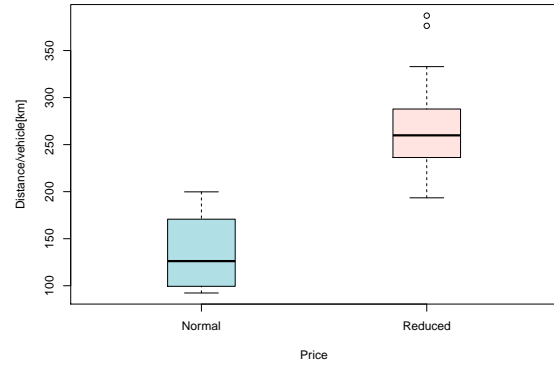

Fig. 12. Daily distances covered by PAVs with a passenger on board for the scenarios with 30m/s speed, 60sec liftoff time and 120sec access time, with the minimized both number of vehicles and empty mileage distance.
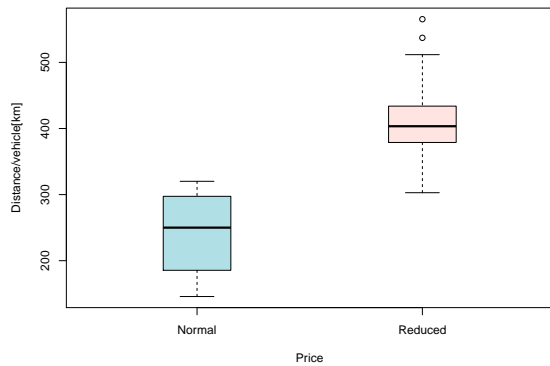

Fig. 11. Daily distances covered for the scenarios with 30m/s speed, 60sec liftoff time and 120sec access time, with the minimized both number of vehicles and empty mileage distance.

currently envisioned price of 4CHF/km is crucial in order to attract short distance users. What was however not discussed so far, but needs to be pointed out are the limitations of the approach presented here and further venues for research.

A. VOT sensitivity analysis for PAVs

Given that the value of travel time of this novel transportation mode is currently not known, a value equal to the public transport value of travel time is assumed in this study. Studies on autonomous vehicles using stated preference surveys have shown that the value of travel time for this mode is in-between that of the private conventional car and public transport [28], [29] and sometimes very close to the value of travel time of the public transport services [30]. Therefore, the assumption to take the value of VOT for PAV service equal to the one of public transport is justifiable. However, to see the effects of different VOTs on the demand, additional simulations are carried out with VOTs for PAVs ranging between those of public transport and conventional car. The increase of VOT as expected triggers a decrease in the amount of rentals. An increase of 4.3%, 8.6%, 13.2% and 17.9% (which corresponds to the VOT of a conventional vehicle) decrease the amount

of rentals by 3.4%, 6.7%, 10.2% and 12.7% respectively. Important to notice is that as the VOT raises the marginal drop of PAV trips decreases.

B. Limitations

Several simplifications were made in the simulation of aerial vehicles. PAVs were traveling in a straight line between the origin and destination, thus not considering no-fly zones, population densities, weather conditions, topography. In order to overcome this a simple detour factor could be incorporated into the simulation. More accurate distance estimation however, would require a tight collaboration with researchers developing the aerial networks that can take different constraints into account [22].

Infrastructure like landing platforms, parking locations or ground communication devices are not taken into account. All these can limit the demand and influence the operational costs. In case the PAVs are designed to land on landing platforms and not in backyards or streets, proper design and planning is necessary. Location of the landing platforms can have a substantial effect on the demand. In already built cities this can pose a problem if there is not available space to place such structures.

Capacities of PAVs in our study was assumed to be 1 for two reasons. Firstly, because most of the current PAV designs are expected to carry one or two passengers. Secondly, because the goal of the paper was to observe the maximum potential demand for this kind of service, therefore PAV service was accessible to every agent in the study area. However, even though the average occupancy of a car is close to 1 in peak hours this might not be the case for PAVs, especially if they have a higher cost, so it might be preferable to share a ride. Therefore, a more detailed system would need to be implemented in MATSim in order to be able to deal with this level of detail.

Here, the benefits of the interaction between ground autonomous vehicles and PAVs was not investigated since the goal of this study was to solely look at the potential demand for PAVs. However, if the PAVs would require landing stations,

the PAV service might benefit of having autonomous vehicles moving people to and from these stations. This will increase the accessibility of PAV service, so the access time can be in order of minutes. A very detailed autonomous vehicles extension of MATSim already exists, so it would be important to pair these two strands of transportation and see how they can impact, benefit and complement each other.

VI. Conclusion

In this study a glimpse at the future of transportation systems with the introduction of on-demand urban air mobility is presented. More than 60 simulations are carried out to investigate how variations in the PAV concept design can influence the demand for this novel transportation mode. The findings show that with the low level of automation and prices set to Uber Black prices, the demand is rather low and the PAVs would mostly serve mid-distance trips. These trips are usually over terrains with obstacles, like lakes, hills or mountains. Importantly, the results also show that unlike for car and public transport services, the vehicle parameters of PAVs have a substantial impact on the demand and turnover. With the reduction of variable costs for the users an increase in the number of trips as well as turnover for the operator is observed. It must be however, pointed out that this does not necessarily mean an increase of profit since many aspects need to be considered in order to provide a clear evaluation.

Optimization procedures show that both minimization of the fleet size in order to reduce the fixed costs for the operator as well as the minimization of empty mileage to reduce variable costs is required. This enables operators to chose from a higher range of PAVs as the required range of vehicles becomes smaller.

Future work needs to be focused on more detailed implementation of the PAVs in MATSim. Infrastructure requirements like number of landing and parking spaces, proper flying corridors, interaction with other modes need to be developed.

Of importance is also the interaction between autonomous ground vehicles and PAVs and how these two future modes can benefit and complement each other. The combination of these two systems might allow for substantial decrease of congestion and negative effects of pollution if planned and implemented in a right way.

Despite the above mentioned limitations this research gives important insights into how the demand for PAVs can be affected by different vehicle parameters. The methodology and results obtained provide a backbone for further research on urban air mobility solutions.

Acknowledgment

References

[1] D. Schmitt and V. Gollnick, "Historical development of air transport," in *Air Transport System*. Springer, 2016, pp. 19–38.

[2] TomTom , "Congestion in Mexico City," webpage, December 2017. [Online]. Available: www.tomtom.com/

[3] A. Horni, K. Nagel, and K. W. Axhausen, Eds., *The Multi-Agent Transport Simulation MATSim*. London: Ubiquity, 2016.

[4] X.-Y. Ni and D. J. Sun, "Agent-based modelling and simulation to assess the impact of parking reservation system," *Journal of Advanced Transportation*, vol. 2017, 2017.

[5] J. Auld, M. Hope, H. Ley, V. Sokolov, B. Xu, and K. Zhang, "Polaris: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations," *Transportation Research Part C: Emerging Technologies*, vol. 64, pp. 101–116, 2016.

[6] C. Rodier and S. A. Shaheen, "Carsharing and carfree housing: predicted travel, emission, and economic benefits," in *83rd Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2004.

[7] SIMMOD, "SIMMOD," webpage, July 2017. [Online]. Available: www.airporttools.com

[8] AirTop, "AirTop," webpage, July 2017. [Online]. Available: www.airtopsoft.com

[9] RAMSrams, "RAMSrams plus," webpage, July 2017. [Online]. Available: www.ramsplus.com

[10] S. Alam, H. A. Abbass, and M. Barlow, "Atoms: Air traffic operations and management simulator," *IEEE Transactions on intelligent transportation systems*, vol. 9, no. 2, pp. 209–225, 2008.

[11] K. Bilimoria, B. Sridhar, G. B. Chatterji, K. Sheth, and S. Grabbe, "Facet: Future atm concepts evaluation tool," *Air Traffic Control Quarterly*, vol. 9, no. 1, pp. 1–20, 2001.

[12] C. Bongiorno, S. Miccichè, M. Ducci, and G. Gurtner, "Elsa air traffic simulator: an empirically grounded agent based model for the sesar scenario," *Proceedings of The Fifth SESAR Innovation Days EUROCONTROL.(Bologna, 3-5 December 2015, Italy)*, 2015.

[13] D. Grether and K. Nagel, "Agent-based modelling of air transport demand," in *World Conference of Air Transport Research Society (ATRS)*, 2013.

[14] J. Bischoff and M. Maciejewski, "Simulation of city-wide replacement of private cars with autonomous taxis in berlin," *Procedia computer science*, vol. 83, pp. 237–244, 2016.

[15] S. Hörl, "Agent-based simulation of autonomous taxi services with dynamic demand responses," *Procedia Computer Science*, vol. 109, pp. 899–904, 2017.

[16] K. Neubauer, D. Fleet, F. Grosoli, and H. Verstynen, *Unmanned Aircraft Systems (UAS) at Airports: A Primer*. Washington, D.C.: The National Academies Press, 2015.

[17] Airbus, "Airbus," webpage, July 2017. [Online]. Available: http://www.airbus.com/newsroom/press-releases/en/2017/06/VSR700.html

[18] Amazon, "Amazon," webpage, July 2017. [Online]. Available: https://www.amazon.com/Amazon-Prime-Air/b?node=8037720011

[19] SwissPost, "SwissPost," webpage, July 2017. [Online]. Available: https://www.post.ch/en/about-us/company/media/press-releases/2017/swiss-post-drone-to-fly-laboratory-samples-for-ticino-hospitals

[20] Uber, "Uber," webpage, July 2017. [Online]. Available: https://www.uber.com/elevate.pdf

[21] M. Shamiyeh, J. Bijewitz, and M. Hornung, "A Review of Recent Personal Air Vehicle Concepts," in *Aerospace 6th CEAS Conference*, no. 913. Bucharest: Council of European Aerospace Societies, 2017, pp. 1–16.

[22] M. Balac, A. R. Vetrella, and K. W. Axhausen, "Towards the integration of aerial transportation in urban settings," in *97th Annual Meeting of the Transportation Research Board*, TRB, Ed. Washington, D.C.: Transportation Research Board, January 2018.

[23] J. Kelemen, "The agent paradigm," *Computing and Informatics*, vol. 22, no. 6, pp. 513–520, 2004.

[24] S. Hörl, M. Balac, and K. W. Axhausen, "A first look at bridging discrete choice modeling and agent-based microsimulation in matsim," *Procedia Computer Science*, vol. 130, pp. 900 – 907, 2018.

[25] C. Weis, M. Vrtic, K. W. Axhausen, and M. Balac, "Sp-befragung 2015 zum verkehrsverhalten," Tech. Rep., 2016-09.

[26] R5, "R5: Rapid Realistic Routing on Real-world and Reimagined networks," webpage, December 2017. [Online]. Available: github.com/conveyal/r5#r5-rapid-realistic-routing-on-real-world-and-reimagined-networks

[27] P. M. Bösch, K. Müller, and F. Ciari, "The IVT 2015 baseline scenario," in *16th Swiss Transport Research Conference*, STRC, Ed., Ascona, April 2016.

[28] F. Steck, V. Kolarova, F. Bahamonde-Birke, S. Trommer, and B. Lenz, "How autonomous driving may affect the value of travel time savings for commuting," in *97th Annual Meeting of the Transportation Research*

Board, TRB, Ed. Washington, D.C.: Transportation Research Board, January 2018.

[29] F. Becker and K. W. Axhausen, "Predicting the use of automated vehicles for Zurich, Switzerland," in *15th Internation Conference on Travel Behavior Research*, Santa Barbara, July 2018.

[30] K. Winter, O. Cats, K. Martens, and B. van Arem, "A stated-choice experiment on mode choice in an era of free-floating carsharing and shared autonomous vehicles," in *96th Annual Meeting of the Transportation Research Board*, TRB, Ed. Washington, D.C.: Transportation Research Board, January 2017.

Milos Balac received his M.Sc. degree in Electrical Engineering from the EPFL. He is currently pursuing the Ph.D. degree at the Institute for Transport Planning and System at the ETH Zurich. His main interests lie in agent-based models, modeling sustainable modes of transportation, transport demand estimation and optimization.

Amedeo R. Vetrella received his M.S. degree in Aerospace Engineering in 2014 at the University of Naples Federico II where he also obtained his Ph.D. in 2018. His research activity deals with cooperative autonomous UAVs navigation in both GPS-challenging or GPS-denied environments.

Raoul Rothfeld received his B.A. degree in Aviation Management from the University of Applied Sciences Bad Honnef - Bonn and his M.Sc. degree in Software Development from the University of Glasgow. He is currently pursuing his Ph.D. degree at the Technical University of Munich while working as a research associate at Bauhaus Luftfahrt e. V., focusing on novel transport concept modelling.

Basil Schmid received his Masters of Arts and Economics from the University of Zurich. He is currently pursuing a Ph.D. at the Institue for Transport Planning and Systems at the ETH Zurich. His main focus is on discreet choice models application in transportation science.