Bi-level Network Design for UAM Vertiport Allocation Using Activity-Based Transport Simulations

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Bi-level Network Design for UAM Vertiport Allocation Using Activity-Based Transport Simulations

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ABSTRACT: The design or the optimization of transport systems is a difficult task. This is especially true in the case of the introduction of new transport modes in an existing system. The main reason is, that even small additions and changes result in the emergence of new travel patterns, likely resulting in an adaptation of the travel behavior of multiple other agents in the system. Here we consider the optimization of future Urban Air Mobility services under consideration of effects induced by the new mode to an existing system. We tackle this problem through a bi-level network design approach, in which the discrete decisions of the network design planner are optimized based on the evaluated dynamic demand of the user's mode choices. We solve the activity-based network design problem (AB-NDP) using a Genetic Algorithm on a multi-objective optimization problem while evaluating the dynamic demand with the large-scale Multi-Agent Transport Simulation (MATSim) framework. The proposed bi-level approach is compared against the results of a coverage approach using a static demand method. The bi-level study shows better results for expected UAM demand and total travel time savings across the transportation system. Due to its generic character, the demonstrated utilization of a bi-level method is applicable to other mobility service design questions and to other regions.

KEY WORDS: network design problem, urban air mobility, vertiports, multi-agent transport simulation

1. INTRODUCTION

Network design problems (NDP) have been a research subject for a long time (1, 2). They are relevant to many different domains, including transportation, telecommunications, logistics, and economics, to name a few. Especially with the changing mobility landscape and the emergence of new multi-modal transport systems, the network design question is still very relevant. One complexity of network designs is that on first sight some effects can seem counterintuitive. See Braess' Paradox, which demonstrates how the overall traffic flow can be slowed by adding more roads to a transport network.

Network design investigations can be grouped according to their degree of including transport dynamics, ranging from approaches focusing on methodological aspects to holistic representation of multi-stakeholder aspects. The first group of methods for solving NDPs (3) can be described as single-level approaches that investigate network designs, with only static or partial dynamic information of the transport system, often used when examining optimization algorithms (4,5). The second group utilizes bi-level approaches that also incorporate the supply side of the transport system in the design process through models or simulation methods, including dynamics as congestion effects and sometimes also an adaption of the agents' route choices during the design process. A third group for solving NDPs are the bi-level approaches that incorporate also dynamic demand information of the transport system in addition to including the dynamic supply side. The demand is adapting in response to the utilization of the supply system. This allows designing mobility services in a multi-stakeholder transport system scenario with conquering services. The proposed method belongs to the last category, including the system dynamics of co-existing systems for the network design process.

The authors of this study propose a bi-level optimization framework to solve the facility location problem at the example of the distribution of Urban Air Mobility (UAM) vertiports. The proposed framework is not limited to urban applications it can be applied to regional scenarios, as shown later in this study. The bi-level investigation consists of two optimization processes linked and performed alternatingly. On the outer loop for the network optimization, a Genetic Algorithm (GA) is used with the Pareto optimal Non-Dominated Sorting Genetic Algorithm (NSGA-II) method to identify the best positions for UAM vertiports. The generated solutions are evaluated on a large-scale activity-based transport simulation (MATSim) within the inner loop, as shown in Fig. 1. In this inner loop a Co-Evolutionary Algorithm (CEA) based optimization is performed within MATSim to adapt the

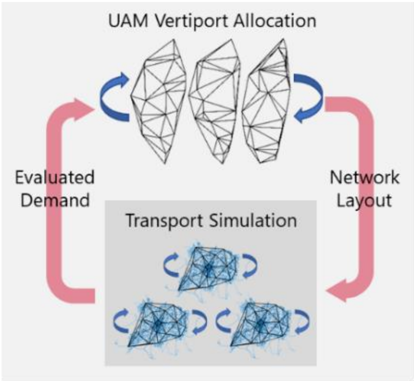

Fig. 1 Proposed bi-level optimization framework: UAM vertiport allocation on outer the layer and transport simulations on the inner layer.

agents' activity plans reflecting the induced network changes. The agents aggregated activity patterns are afterward used for re-evaluating the network design. This bi-level approach is allowing to tackle the NDP variant of the Activity-Based Network Design Problem (AD-NDP), by making it possible to include recoupling effects of the transport system on the supply and demand side after adding a new transportation mode effect. Thereby not only the reactions of the affected agents who use the UAM mode but also related effects, e.g., congestions due to network capacity or during rush hours and overall system travel times or resilience, can be incorporated and used as objectives in the design process. This integration enables the decision maker to compare optimized trade-off solutions for scenarios where mobility services must be designed together with multiple stakeholders.

The proposed framework is unique due to combining a bi-level approach for solving the network design problem in a multi-objective optimization approach with a large-scale activity-based transport simulation problem for solving the UAM vertiport placement problem.

2. APPROACH

The activity-based transport simulation method with its CEA optimization is described in 2.1, followed by the multi-objective optimization approach using a Genetic Algorithm to solve the Network Design Problem in 2.2.

2.1. Activity-Based Transport Simulation

The evaluation of the network designs is performed on an open-source platform for Multi-Agent Transport Simulation (MATSim) (6), which uses an activity-based approach that optimizes through a co-evolutionary approach the activity chains for a large number

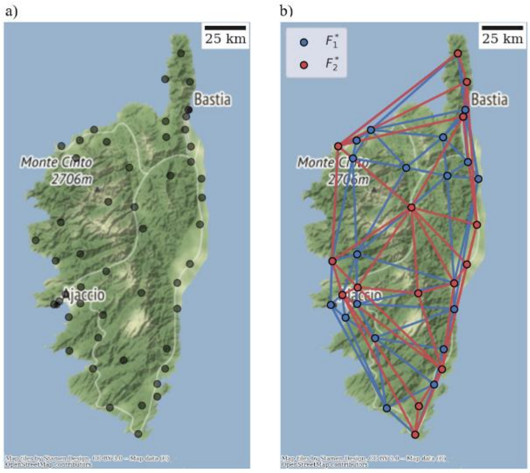

Fig. 2 a) Set of possible vertiport locations based on Corsica's population distribution; b) Multi-Objective Optimization results showing solution for UAM vertiport network with maximum demand (f_1^*) and minimum number of vertiports (f_2^*).

of agents in a 24h period. The MATSim framework and the scenario are open-source, and a description is available (6, 7). For our study, we used the available simulation of the region of Corsica[1] with a 1% representation of the population using about 3400 agents. The agents can choose from the transportation modes car, walk, bike, train and bus to complete their daily activities, depending on individual and spatial accessibility. We extended the available transportation modes with a UAM system through the open-source extension MATSim-UAM from Bauhaus Luftfahrt (8). It allows for adding infrastructure and a transportation mode for an aerial mobility service. The configuration of the aerial vehicles is based on data from the electrical Vertical Take-Off and Landing (eVTOL) database[2], using a mean set of parameters of 4 persons, 500 km range, and 250 km/h cruise speed.

The set of possible vertiport locations is determined beforehand based on the residence locations of the agents. For that, the population is separated into 50 clusters and based on a spatial mean center, possible vertiport locations are derived as shown in Fig. 2 a). This reflects a realistic constraint of the existing infrastructure.

The optimized activity chains for each agent are explored within MATSim's activity-based simulation. This is accomplished through a CEA approach by mutating, e.g., transportation modes, start and end times, and activity orders. The generated activity chains are evaluated based on a utility function, which is, among other criteria, assessed on the travel time, including transfer times towards transportation hubs, e.g., Vertiports for using UAM, the

[1] github.com/matsim-scenarios/matsim-ile-de-france
[2] evtol.news/aircraft, accessed 20.01.2022.

processing times within a transportations service, e.g., waiting times for public transport vehicle to arrive or service time for checking in and out. The fleet management of eVTOLs can be specified within the MATSim-UAM extension, and each vertiport can have a defined number of initial eVTOLs parked. During simulation, once a request at a station is registered, a vehicle is reserved for the agent, first come, first out. For our scenario, we relaxed the fleet representation of having a limited number of vehicles per station and binned passengers registering within a 20-minute time window for joint trips to estimate the required number of vehicles.

Iteratively, each agent's activity chain is optimized based on a utility function calibrated initially on available data of the city's transport system. The utility function includes, among others also, time-dependent and independent utility contributions for each transport mode. A detailed explanation of the design and calibration of the utility functions is described in [6,7] respectively. The optimization is terminated when the average utility value within the transportation system converges, which indicates that the agents cannot find a better solution. The transport system has then reached a stable equilibrium state.

2.2. Facility Location Problem

The following problem belongs to the facility location problems, a subclass of the NDPs, which targets distributing UAM vertiports by locating supply nodes in a transportation network to serve a nearby demand best. Comprehensive overviews of existing variants, including applications, are available from the literature (1, 3). In contrast to non-bi-level approaches where the static demand is estimated a priori through models or simulations, our approach derives the demand individually for each network adaption from the bi-level activity-based simulation.

Within the outer loop of the bi-level approach a multi-objective problem formulation is used. The idea of the formulated objectives is to help operators in designing a UAM network that on the one side is built to maximize the service utilization and on the other side minimizes the number of active vertiports for making the service as efficient as possible. The first objective, the overall UAM transportation demand maximization is formulated as

$$\max f_1 = \sum_{j \in N} d_j$$

with the UAM mode demand being d_j for station j. The second objective to minimize the number of active UAM vertiports with x_j being 1, if a facility is located at node j and 0 otherwise. The previously defined set of possible vertiports locations is N, such that $x_j \in \{0,1\}, j \in N$ and the objective being:

$$\min f_2 = \sum_{j \in N} x_j.$$

The constraint for the number of active ports is thereby limited to be $P = 25$, where P is defined as $\sum_{j \in \mathrm{N}} x_j \leq P$.

For comparison, we chose a frequently used Heuristic Coverage Method (HCM) approach as baseline. The set of active facilities is optimized with the goal to maximize the number of agents within a predefined covering distance of an active vertiport. A description of the implementation can be found in literature (2).

3. EVALUATION

Optimizing the facility location problem in the outer loop was performed on 50 generations with a population of 10 each. The co-evolutionary optimization within MATSim was performed for each of the arround 3400 agents. The co-evolutionary optimization process is terminated when a system equilibrium is reached, indicated through the utility value. For our study, the number of optimization steps within a simulation is limited to ten iterations. The parameter's average trip distances and trip durations in Fig. 3 during those iterations provide insight into the system's changes to transport characteristics. The total time traveled decreased while the total distance traveled increased. This on-first-sight unintuitive behavior is grounded in the initial path generation being based on a shortest path algorithm. During optimization, the chosen routes are replaced routes with improved utility can be found. Therefore, among other parameters, the route choice, modal choice, and activity sequence are adapted [6]. This leads to the agents finding improved paths that, among other things, allow a faster transport to their goal but may require longer travel distances. For our study,

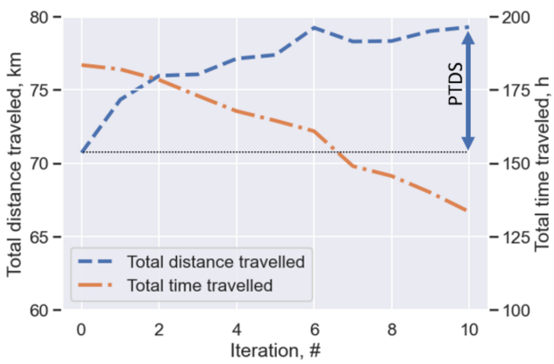

Fig. 3 Aggregated distance and time traveled of all agents with Potential Travel Distance Savings (PTDS).

we chose that the travel distance saturation marks a satisfactory system stability to be used for solving our facility location problem.

The difference between the total distance traveled in the first and tenth iteration shows the Potential Travel Distance Saving (PTDS) of an existing network. From the user's perspective, in an ideal traffic scenario, one could take the shortest route with the shortest travel time, and the PTDS would be zero.

3.1. Results

The non-dominated solutions found by the NSGA-II are $f_1 \in [0,1]$ and $f_2 \in [15,25]$. f_1 is normalized by a maximum UAM demand of 187. The set of Pareto solutions can be found in Fig. 4, with a normalized f_1. The non-dominated solution for f_1 can be derived at the Pareto endpoint $F_1^* = (1.0, 25)$ with a vertiport network of 25 active ports. The non-dominated solution found for f_2 is $F_2^* = (0.4, 15)$ with a demand of 40 % and 15 active vertiports. Both found UAM network layouts for F_1^* and F_2^* are shown in Fig. 2 b). The network design for both networks shows that the overall reach from north-south and east-west is similar despite F_1^* having ten additional active vertiports. The network layout F_2^* suggests that the maximum demand with only 15 vertiports can be achieved by a network covering long distances at the coastal areas.

A knee point solution within the Pareto set for the shown weighted approach would be $F_k^* = (0.9,19)$. This trade-off solution balances the minimization of vertiports and the demand and allows finding profitable service designs if cost and revenue structures are integrated into the parameterization. The corresponding network layout for F_k^* is shown in Fig 5 b). The network maintains a similar north-south and east-west reach as F_1^* and F_2^* but with only 19 vertiports it has a different configuration in between.

To compare the bi-level approach AB-NDP with the static facility location approach HCM, the HCM is applied on a single

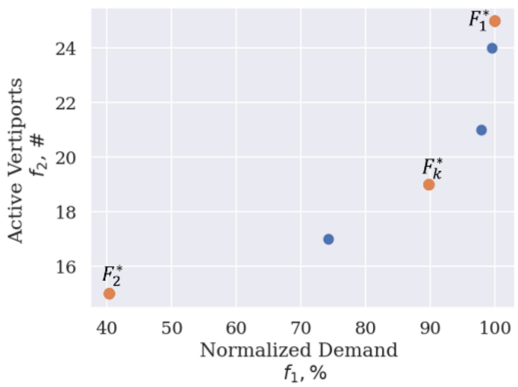

Fig. 4 Found solutions of the NSGA-II in the Pareto set.

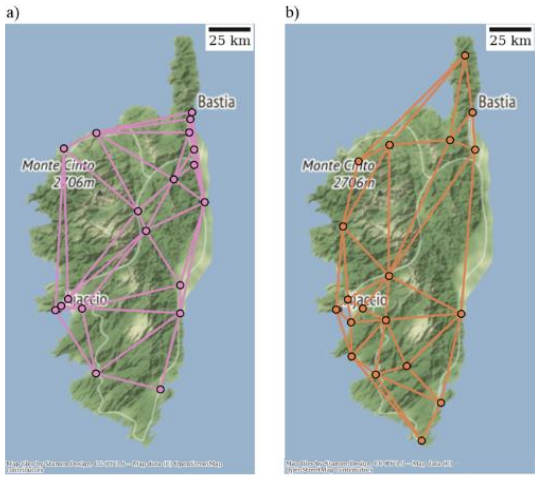

Fig. 5 UAM networks with 19 vertiports a) Heuristic Coverage Method (HCM) b) tradeoff solution of bi-level optimization F_k^* (AB-NDP).

iteration of the simulation. For comparison, the number of vertiports is specified to the number found for the knee point solution $F_k^*(:,19)$.

The UAM demand shown in Table 1 is normalized with the maximum found UAM demand from F_1^*. The Total Travel Time Saving (TTTS) are the aggregated travel times across all modes. The travel times are normalized with the total travel time without a UAM transportation mode being available.

The solution from the AB-NDP approach shows a higher UAM demand than the HMC approach's solution by 19 %. The HMC UAM network in Fig. 5 a) indicates a more compact design than F_k^* from Fig. 5 b). This is partly due to the HMC relying only on static locational information. In contrast, the AB-NDP has additional dynamic information about the activity locations of the agents, e.g., about their work, educational, or leisure areas, that are indirectly utilized within the bi-level framework. Additionally, the comparison of TTTS shows an improvement compared to a transport system without a UAM transportation mode. For the AB-NDP solution, the TTTS will increase by around 7.27 %, whereas for the HMC, it will only increase by 5.65 %. This shows the UAM transportation mode's effect beyond solving the vertiport location problem.

The bi-level optimization framework AB-NDP shows better results than the HMC method for the investigated parameters and positively affects the overall transportation system.

Table 1 UAM demand normalized with F_1^*; Total Travel Time (TTT) normalized with TTT w/o UAM mode.

	Demand, %	TTTS, %
AB-NDP ($\boldsymbol{f_k^*}$)	89.98	7.27
HMC	70.97	5.65

4. CONCLUSION

Within this study a new bi-level approach was proposed to solve the facility location problem from the AB-NDP group with a large-scale, open-source transport simulation at the example of finding optimal positions for UAM vertiports. The NDP was solved with an NSGA-II approach investigating the objectives of minimal network size and maximum UAM demand. When parameterized correctly, the method allows designing a service to cover a maximum demand with a minimum network size. The demand was derived through the activity-based transport simulation MATSim. The dynamic demand changes and their effects on the transport supply network were incorporated into the design process.

An HCM without a bi-level coupling was used for comparison as a baseline. The results from the activity based approach were superior for the investigated mode-specific UAM demand and transportation system-wide TTTS benchmark parameters.

Although adding a large-scale traffic simulation to a classical network design problem increases complexity by requiring additional expertise for activity-based simulations, it enables a holistic approach by incorporating co-existing system stakes into the mobility service planning process. Particularly for network design problems strongly influenced by the infrastructure of other transportation systems, like sharing or swapping services, the bi-level approach presented can provide a solution to design a service that is integrated into an existing multimodal transportation network.

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