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Data-driven Evolutionary Optimization of eVTOL Design Concepts Based on Multi-agent Transport Simulations

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Electric Vertical Take-Off and Landing (eVTOL) aircraft design concepts are currently developed by many companies and research consortia. An essential topic in the development process is finding the optimal vehicle specification very early on to identify the designs that promise the best fleet operation profit. This paper proposes a novel method that combines open vehicle design concepts with an Evolutionary Algorithm (EA) optimization scheme to find the optimal aircraft specifications, including capacity, range, cruise speed, and height. The proposed optimization framework is evaluated using an activity-based large-scale multi-agent transport simulation for the region of Corsica. The results show that the framework yields different design concepts for different Urban Air Mobility (UAM) network designs. A significant increase in the expected profit can be obtained by adapting the vehicle specification for specific market conditions. This shows the potential of the proposed method, which, through its generic character, could be applied in the future to determine optimal configurations of different products and services for particular markets by maximizing the profit of the fleet operator and the overall utility of the customers.

I. Introduction

In the future, urban and regional air mobility promises to play an increasingly important role in the transport of people and goods in dense metropolitan areas. To date, various companies and research consortia have produced a wide range of different vehicle concepts, and it still needs to be determined which of these will best serve the demands of all the stakeholders involved. Therefore, one critical question for fleet operators is how to find the optimal vehicle specifications for a specific region by considering existing transportation systems. Urban Air Mobility (UAM) vehicle specifications like maximum range, speed, or capacity will affect mobility service parameters and determine the operator's profitability depending on the specific situation. Hence, determining optimal vehicle specifications for a particular problem early on can be valuable when planning UAM systems.

We present a framework to identify the optimal UAM vehicle design based on large-scale multi-agent mobility simulations. We, therefore, integrate a Genetic Algorithm (GA) optimization scheme and a co-evolutionary based multi-agent mobility simulator, MATSim [1], with a UAM service extension [2] for the region of Corsica. To identify the design space of possible Electric Vertical Take-Off and Landing (eVTOL) vehicle specifications, we utilize a large number of publicly available design concepts from an open data set [3]. As a result, the dimensionality of the search space can be considerably reduced, and unrealistic eVTOL models are excluded from the analysis already on the representation level. Similar approaches with different optimization and demand predictions have been proposed to address problems related to the design of eVTOL vehicles [4, 5]. The proposed framework is unique due to combining a data-driven approach to identify the relevant design space for eVTOL concepts and utilizing a large-scale transport simulation for evaluating the found configurations. Therefore, it is not required to have a full system model early on, and it also allows considering transport dynamics due to the agent's behavior changes in the design process early on.

II. Related Work

Traffic Simulation

There are a variety of frameworks to simulate urban or regional traffic, ranging from microsimulations with a high spatial resolution, like Sumo [6], to macroscopic simulators based on aggregated traffic flow characteristics, like PTV Visum [7]. There are also simulators, like MATSim, located at the boundary between the two former types. Here,

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vehicle movement is often simulated through queue approaches, and vehicles are moved between such queues. Another distinctive characteristic is the modeling methodology. There are several approaches, one being the four-step model based on the steps: trip generation, trip distribution, mode choice, and assignment, as used by PTV Visum. Furthermore, there are activity-based models, such as MATSim, based on replicating and linking trips of many agents and modeling them as part of larger daily activity patterns. While each framework has its advantages and disadvantages, for the scope of this study, MATSim was chosen because the activity-based approach allows the inclusion of the transport system dynamics caused by the agent's aggregated behavior into the design process. Furthermore, an available extension for UAM modeling [2] allows the integration of UAM systems in the simulation. Recent studies applied the framework to investigate the potential of a UAM transport mode for several urban areas [8, 9].

Aircraft Design

A standard method in design frameworks combines the governing physical equations, e.g., aerodynamic or energetic equations, as constraints and an optimization method to derive an optimal design specification. Several studies are also available for UAM vehicle designs for different system parts. In [10], the authors investigate different vehicle types as tilt-rotor, tilt-wing, and lift + cruise, with the help of detailed physical models that require up to 19 design parameters as input configuration. This representation was extended by [11] to include even fixed and wingless designs into the framework. In [12], multiple vehicle architectures, which are generated from detailed physical models, are used for investigating the different sizes and powertrain specifications. It quickly becomes apparent that to derive a realistic design parameter space, a full physical UAM vehicle model is required, and therefore a large number of physical and configuration input parameters are needed [10]. To overcome the requirement of complex system models at the beginning of the design process, low-dimensional representations based on data-driven approaches can be used [13]. The approach presented in this paper does not attempt to build an detailed physical model for all relevant systems. Instead, we aim to derive a parameter design space from the UAM vehicle specifications published in recent years. This is possible thanks to the availability of UAM vehicle specification databases [3] from which we process the most relevant specification parameters for determining regression functions in Section III.B.

III. Framework and Experimental Setup

The proposed framework is split into several steps, see Fig. 1. First, to narrow down the design space to feasible vehicle concepts, a publicly available data set [3] is utilized and post-processed. Then regression models are built based on the characteristics of the data set and linked to the different vehicles. The data set extraction and generation of regression functions are only necessary once at the beginning of the optimization process. Afterwards, the eVTOL configurations can be derived based on the regression functions. For quantification of the success of the different UAM specifications, an operating profit is evaluated based on the results of the transport simulation for each eVTOL configuration. The objective function for the used GA scheme is based on the number of active UAM vehicles, the distance the UAM vehicles have covered (with and without passengers), and the number of people per vehicle. This is repeated until the optimal eVTOL specifications are found. The results of the presented data-driven approach heavily rely on the availability of eVTOL design data sets, which would significantly improve with realistic and validated vehicle designs being generated and available, e.g., known from the car domain [14].

A. Optimization Problem Definition

A simple profit estimate from the perspective of the operator of the UAM fleet is used as an objective function to optimize the vehicle specification. In the optimization scheme the fitness value refers to the predicted profit. The database is derived from a publicly available data collection of projected revenues, costs per kilometer, and the initial vehicle acquisition costs. Here, revenue R_{total} is estimated using the passenger-kilometer specific cost $\alpha_{\text{rev}} = 1.18\,\frac{€}{\text{km}}$ [15],

$$R_{\text{total}} = d_{\text{P}}\alpha_{\text{rev}}, \tag{1}$$

where, d_{P} refers to the total passenger-kilometers traveled in all UAM vehicles. The total cost C_{total} is calculated using the specific cost parameter $\alpha_{\text{cost}} = 4.13\,\frac{€}{\text{km}}$ according to

$$C_{\text{total}} = n_{\text{V}}(d_{\text{V}}\alpha_{\text{cost}} + C_{\text{unit}}). \tag{2}$$

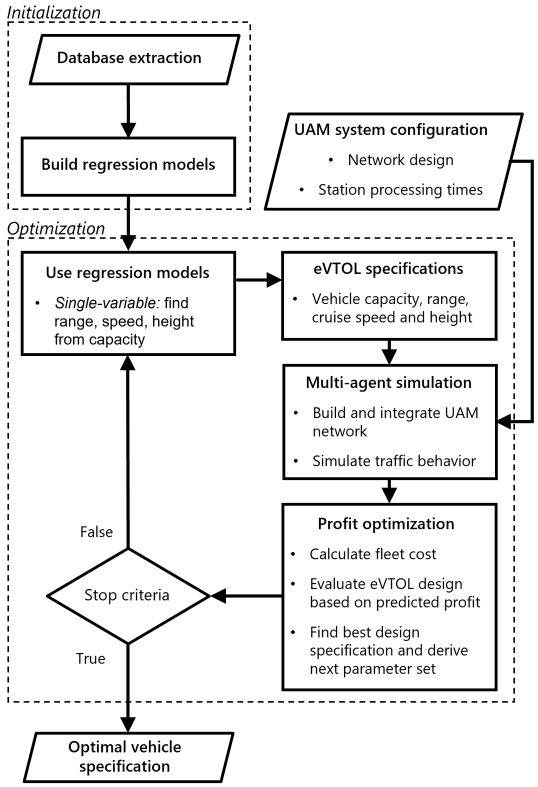


Fig. 1 Flow diagram of the proposed integrated optimization framework.

Here, n_V refers to the number of vehicles used, d_V are the vehicle kilometers covered, and C_{unit} is the unit cost per vehicle. The unit cost function is based on a linear regression from the available data points. The unit price for the first vehicle is set according to the projections from [15] equal to $C_{u1} = 2 \times 10^6$ € with a passenger capacity of $c_{u1} = 6$ PAX. We took the estimated cost of another UAM vehicle with a capacity of $c_{u2} = 1$ passenger and a predicted unit cost of $C_{u2} = 4.5 \times 10^5$ € (average taken from [16], [17]) as a second data point. Thus, C_{unit} can be calculated for the respective capacity c according to

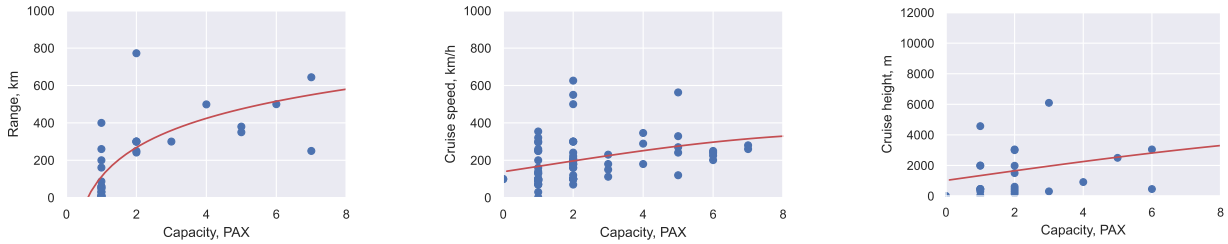
$$C_{unit} = \gamma_1 c - \gamma_2 \tag{3}$$

with $\gamma_1 = 4.4 \times 10^5$ and $\gamma_2 = 4.3 \times 10^5$. From equations (1) – (3), the objective function, profit P corresponding to $P = R_{total} - C_{total}$, can be obtained. Due to sparseness of the available data sets, this can only be a very simple estimate about the unit costs based on the vehicle's passenger capacity. With increasing availability of eVTOL design information and proprietary information of the operators, the accuracy of the method will improve. The optimization problem is defined as:

$$\begin{aligned} &\max_{\mathbf{z}} P(\mathbf{z}); \\ s.t.\ &1 \leq c \leq 8\,\text{PAX}, \\ &0 \leq r \leq 1000\,\text{km}, \\ &0 \leq u \leq 600\,\text{km/h}, \\ &300 \leq h \leq 10\,000\,\text{m}, \end{aligned} \tag{4}$$

with $\mathbf{z}$ depending only on the vehicle's passenger capacity $\mathbf{z} = c$ and the vehicle's range $r(c)$, speed $u(c)$, and cruise height $h(c)$ being determined through the regression functions by the capacity.

The optimization problem is solved using a GA [18] and is implemented through the *deap* framework [19] in Python as a binary-encoded problem. A common parameterization with a random-based selection strategy (*selRoulette*), a crossover of $p_{CXPB} = 0.8$ and a mutation probability of $p_{MUTB} = 0.2$ is chosen.



(a) **(b)** **(c)**

Fig. 2 The regression functions for UAM vehicle specifications: range (a), speed (b), and cruise height (c) are given with regard to the UAM vehicle capacity as number of passengers (PAX). The regression models were developed using the Gaussian Regression Method [20]. The dataset of UAM vehicle parameters is not fully populated. Therefore, there is a inconsistent number of data points per correlation.

B. Regression

Based on the found aircraft specifications, combinations of parameter pairs were investigated for their correlation quality. For finding the best parameters for an abstract representation of an eVTOL vehicle, all available parameters were compared by the frequency of their occurrences for each vehicle type and their relevancy for system representation. For those reasons, we used the UAM vehicle parameters of flight distance, the number of passengers, cruise speed, and cruise altitude to represent the available vehicle types. The vehicle's transport capacity was determined as the regression variable since it is the parameter with the highest availability in the extracted database and represents better correlations in comparison.

For this purpose, the regression functions for flight range (a), flight speed (b), and flight altitude (c) are derived as a function of the number of passengers (Fig. 2). The representation is on the abscissa for $1-8$ passengers and on the ordinate for a flight range of $0-1000\,\mathrm{km}$, vehicle speed of $0-600\,\mathrm{km/h}$ and cruise height $0-10\,\mathrm{km}$. It is shown that the number of data points is non-uniform between the different regressions due to the inhomogeneous database entries, and the highest number of specifications is observed for a low number of passengers. Also, the highest spread can be observed for a low number of passengers. The regression models were developed using the Gaussian Regression Method [20]. The regression function for the vehicle range in Fig. 2 (a) shows a positive progression with an increasing number of persons, whereas the slope decreases. The vehicle range regression model's Coefficient of Determination (COD) is $COD = 0.21$. The number of data points of travel speed in Fig. 2 (b) have a significantly large spread and a better representation of low numbers of passengers compared to the previous data set. The speed regression function also increases with the number of persons. The speed regression has a score of $COD = 0.17$. The cruise height regression in Fig. 2 (c), like the previous two, shows a slightly positive progression over the number of persons with a regression score of $COD = 0.2$.

For our later introduced *multi-variable optimization*, the coupling of the parameters was relaxed. Only the previously introduced parameter ranges were kept to limit the used design space without using the regression functions directly. Nevertheless, the cost function, which is calculated based on the capacity, requires the equivalent capacity for a specific range, cruise height, or cruise speed. Therefore the inverse regression function is used for deriving a mean passenger capacity for the *multi-variable optimization* in the second part.

The derived regressions cannot match the specification parameters with high accuracy, as the COD indicates. Improving the COD is difficult for different reasons. One is the quality of the acquired data sets: currently, only a few companies have reached a mature stage of developing or producing UAM vehicles. The majority of the specifications are based on estimates at various stages of development and can therefore change until release, or the data itself can be outdated or inaccurate. Another factor lies in the abstract representation of a complex system, e.g. for hybrid-electric aircraft configurations, the UAM specifications (weight, range) depend on the used powertrain architectures and cannot be represented entirely from the small number of publicly available information about UAM vehicle specification [21]. Due to the sparse knowledge of the internal system designs, deriving more specific physical parameters, e.g., energetic comparisons is hard to achieve. However, only these simplifications allow us to utilize a larger number of different UAM systems.

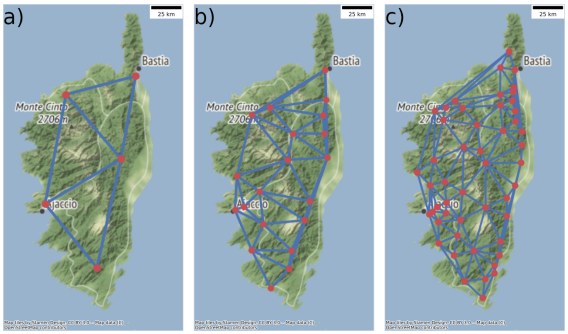


Fig. 3 UAM network distribution on Corsica for 5 a), 20 b) and 50 c) vertiports.

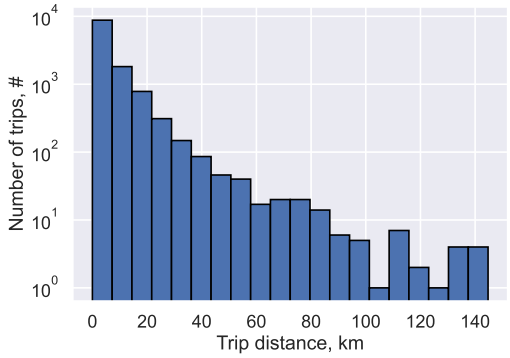


Fig. 4 Histogram of the number of trips the agents performed in relation to the trip distances.

C. Multi-Agent Transport Simulation with MATSim

For the evaluation of the found vehicle concepts, we use an open-source activity-based Multi-Agent Transport Simulation MATSim [1] for the region of Corsica. The activities over a day of 1% of the population are calculated for 3.4×10^3 agents to find the optimal activity pattern and optimal modal choice for each individual agent. The co-evolutionary approach and the generation of a MATSim simulation are described in detail in [1], [22]. We extended the available simulation of Corsica with a UAM mode with the help of the open-source extension MATSim-UAM from Bauhaus Luftfahrt [2]. It adds a new transportation mode to the mode choice of the agents when performing their daily activity tasks. Before starting the simulation, it is required to define the relevant UAM system parameters like the UAM vehicle specifications and UAM network parameters defining the layout and vertiport processing parameters.

Due to the network parameters being external factors that stay unchanged during the optimization but still strongly affect the UAM demand [9], multiple network configurations shall be investigated. The position of the individual stations is determined based on the residence locations of the agents. The population is separated into a defined number of clusters, and for each of them, the mean local center of the residence positions is determined as the vertiport position. The links between the vertiports are designed based on a Delaunay triangulation scheme. Fig. 3 shows three UAM network layouts with 5, 20, and 50 vertiports, which will serve as a basis for the upcoming studies. Further parameters are the processing time for a UAM vehicle at a station and corridor capacities. Corridor refers to a link between vertiports. We defined a baseline for the UAM network parameters and the vehicle specification based on a capacity of four passengers (PAX) with the respective other variables according to the previously introduced regression functions:

- Vehicle range: 499 km
- Vehicle cruise speed: 251 km/h
- Vehicle cruise height: 2.3 km
- Vehicle vertical speed: 50 km/h
- Vehicle capacity: 4 PAX
- Station process time each trip: 30 min

IV. Results

Based on the introduced framework, we investigate the dynamics of the transportation system and their effects on the results of the UAM specification optimization scheme in the following part. Therefore, we first analyze the mobility characteristics specific to the Corsica scenario. We identify the agents' typical trip lengths and the coverage of the simulated UAM networks. Next, we discuss the effect of UAM network size on the optimal vehicle parameters.

A. Mobility Characteristics

We first investigate the accessibility of the UAM vertiports, considering the agent's daily activity plans and residence positions. Previous studies have shown that the UAM network layout has a significant effect on UAM usage [9].

To better understand the demand generated from the agents' activities, the distribution of trip distances across all traffic modes is investigated first, see the histogram in Fig. 4. A majority of the trip distances is < 10 km with an average

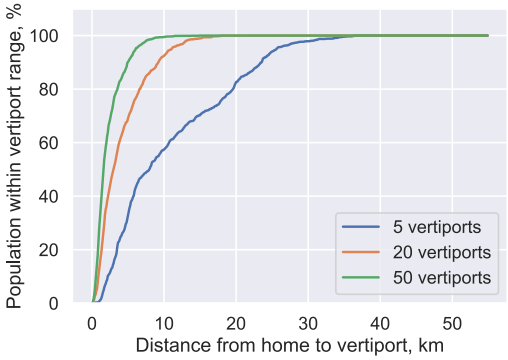


Fig. 5 Coverage of the agents' homes as a function of the Euclidean distance to the nearest vertiport station.

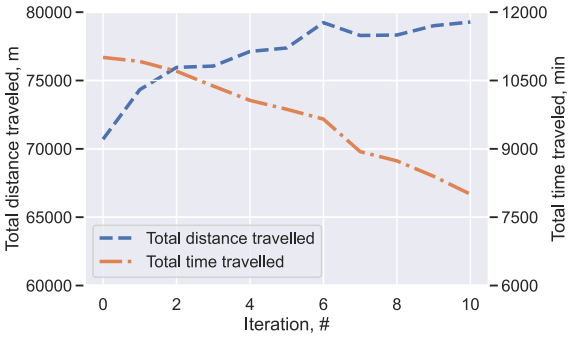


Fig. 6 Total distance and total time traveled for all agents across all modes on a 5 vertiports scenario over the course of ten iterations.

Vertiports, #	MCL (STD), km	STEL, %	Fitness, €
5	71.26 (25.16)	0.56	3.9×10^8
20	63.55 (31.95)	0.73	-2.9×10^7
50	62.91 (33.44)	0.73	-1.1×10^8

Table 1 Configuration comparison of the Corsica scenario. Three network sizes with different vertiport numbers are given with their mean corridor length (MCL) and standard deviation (STD). Alongside the share of the population with trip distances that are equal or larger (STEL) than MCL and the baseline fitness values for each network size in €are shown.

trip length of 6.96 km. This indicates that UAM services will not be relevant for most trips on network sizes investigated in this study. The UAM services will just play a role for a smaller population share covering longer trip distances.

On the network supply side, it is interesting to explore how the network size affects the accessibility of UAM services. Therefore, we analyze the average Euclidean distances between the agents' homes and the closest vertiports and their corresponding share of the total population within a specific range (Fig. 5). As the number of vertiports increases, it is apparent that broader coverage is achieved at much smaller distances. For a UAM network with 50 vertiports, the share of agents that have a vertiport closer than 6.96 km to their homes is 88 %. In contrast, for the network with 5 vertiports, only 49 % of the synthetic population is within an average trip length of a vertiport.

Next, we investigate the Mean Corridor Length (MCL) to bring a second perspective to the discussion about the availability of UAM infrastructure. The MCL allows comparing the trip length with the average UAM corridor length. The MCL for the respective vertiport numbers shows that the agents' average daily trip length of 6.96 km is up to an order of magnitude lower (Tab. 1). Even for the largest UAM network studied, with 50 vertiports, which has the smallest MCL, the Share of agents with Trip lengths that are Equal or Larger (STEL) is 0.73 %. For 5 vertiports the STEL is as small as 0.56 %. Therefore, the implemented UAM service is relevant for only a small fraction of agents in this scenario.

Another noteworthy subject for integrating transport dynamics in the design process is the stability of the traffic simulation and its activity patterns. A co-evolutionary optimization is performed for each individual traffic simulation until a system equilibrium is achieved and the activity patterns converge [1], [23]. The convergence is measured via the trip distances and trip durations. Each simulation was performed ten times, during which the travel distance increased significantly in the first two iterations but gradually approached saturation in the eighth to tenth iteration (Fig. 6). This unintuitive behavior is caused by the initial plans of the agents being based on the shortest path due to not having any information about how long a trip will take before the first simulation iteration. After several iterations, the agents find longer but faster routes for executing their activity plans. Therefore, the total travel hours decrease steadily until the tenth generation. The travel distance saturation marks a good balance between a stable transport system and a resource-efficient simulation, considering that the simulation must be repeated for every individual during the

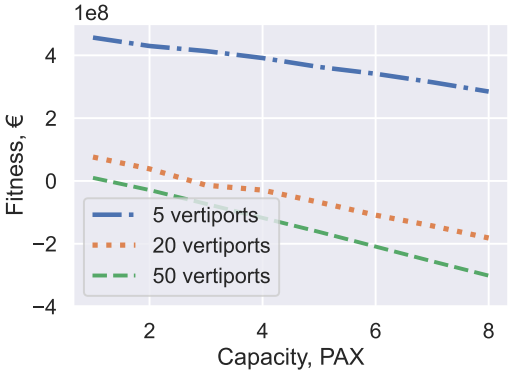


Fig. 7 Fitness values for 5, 20 and 50 vertiports over the course of the optimization parameter vehicle capacity.

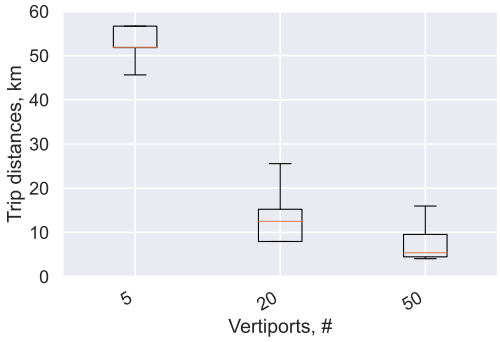


Fig. 8 Trip distance for the three UAM network sizes of 5, 20 and 50 vertiports are shown only for the UAM mode. The whiskers indicate the minimum and maximum, the box the first and third quartile and the orange line the median trip distances.

Vertiports, #	Best fitness, €	Δ-fitness, €
5	4.6×10^8	0.7×10^8
20	7.6×10^7	1.5×10^8
50	9.9×10^6	1.2×10^8

Table 2 Fitness value of best individual w.r.t. baseline fitness for Corsica scenario with 5, 20 and 50 vertiports.

optimization process and is therefore used in the following as the cutoff point of the transport simulation.

B. Regression-based Capacity Optimization

After investigating the mobility characteristics, the GA optimization framework is applied to different UAM network sizes to derive the optimal vehicle specification for each variant. The design variables range, cruise speed, and height are implicitly determined through the optimization variable capacity. We tested the optimization scheme first on the minor problem with only eight possible designs to find the most realistic vehicle specification for different UAM network sizes. Due to its small parameter space, it was sufficient to simulate 20 generations with a population size of 10.

The optimization results for the different UAM network sizes show that the individuals with the highest fitness value are across all network sizes the ones with a UAM vehicle capacity of 1 PAX (Fig. 7). This corresponds to a UAM vehicle range of 187 km, cruise speed 167 km/h, and a cruise height 1.3 km for the best individual. In comparison to the baseline fitness this represents an increase of about 17.9 %. It is also noteworthy that the fitness values decrease and turn negative with an increasing number of vertiports. Nevertheless, after the optimization converges, an improvement of the fitness value is achieved for all UAM network sizes compared to their respective baseline fitness values (Tab. 2). For a UAM network with 5 vertiports, the best individual shows a fitness improvement of 0.7×10^8 €, for 20 vertiports an increase of 1.5×10^8 €, and for 50 vertiports an increase of 1.2×10^8 €, compared to their respective baseline fitness values (Tab. 1). When comparing the best individuals between the different UAM network sizes, it is apparent that a fifty-fold decrease between the 5 and 50 vertiport network indicates that for the investigated scenario the most profitable UAM network configuration would have 5 vertiports.

One reason for the decreasing fitness for larger UAM network sizes is the decreasing average UAM trip length with a similar number of trips. The median trip distance of a UAM vehicle in the 5 vertiport network is 51.9 km with 118 trips. That is more than four times the median trip distance a vehicle in a 20 vertiport network covers, which is 12.5 km with 141 trips. For 50 vertiports, the median UAM trip distance is 5.4 km with 115 trips. This is less than half of the vehicle trip distance compared to the 20 vertiport network (Fig. 8). The fitness of the larger UAM networks is much smaller because the UAM trip distances are strongly decreasing while the number of trips remains constant.

Table 3 ***Multi-variable optimization*** **results: Fitness value of best individual with relative change to base fitness value for Corsica scenario with 5 vertiports.**

Vertiports, #	Best fitness, €	Δ-fitness, %
5	5.25×10^8	+34.6

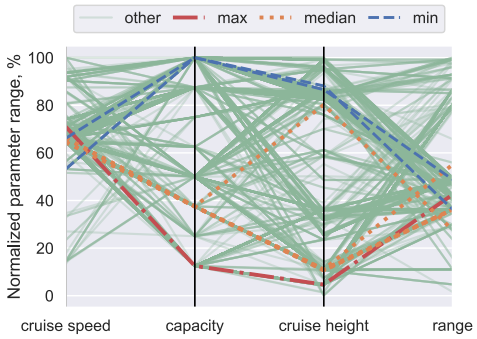


Fig. 9 Multi-parameter optimization results on Corsica with 5 vertiports. The individual optimization parameter sets are shown for the normalized parameter ranges in %, for cruise speed $0 - 600\,\mathrm{km/h}$**, capacity** $1 - 8\,\mathrm{PAX}$**, cruise height** $0 - 10\,\mathrm{km}$ **and range** $0 - 1000\,\mathrm{km}$**. The results are derived from all explored solutions during the optimization process.**

C. Multi-variable Optimization

After using the single parameter optimization to find the best specification from the available UAM concepts, the optimal vehicle's specification will be derived without the regression constraints between the different parameters. Therefore, the parameter space grows significantly due to the multiple combinations of the optimization variables capacity, cruise speed, cruise height, and range.

Even though not relying on the designs and regression functions for the vehicle generation, the *multi-variable optimization* uses the inverse of the regression functions for predicting the UAM vehicle cost. Due to the sparse data about predicted UAM unit costs and, therefore, not being able to derive a cost function for each variable, the vehicle cost is predicted based on a mean vehicle capacity. This capacity value is calculated through the inverse regression functions for the individual specifications. With this modification, the previously introduced unit cost function for different capacity values can be used, as explained in Sec. III.A.

For the *multi-variable optimization* we performed an optimization with 100 generations, 10 individuals each and focused on the UAM network with 5 vertiports due to computational resource constraints. Compared to the baseline configuration, the fitness value could be improved by 34.6% to 5.25×10^8 (Tab. 3). Compared to the best individual from the single variable optimization using the UAM specification regression, its fitness value could be increased by 14.1%. The best-found individual has a capacity of 1 PAX, a range of 108 km, cruise speed 176 km/h, and a cruise height 190 m. Notably, the cruising height is relatively low compared to the previously found best individual with a cruise height of 1.3 km. Even though the number of generations is relatively small for a GA optimization, a significant increase of up to 34.6% in the fitness function can be achieved. For a more realistic view, regulatory requirements and social constraints would have to be taken into account for future evaluations.

For comparing the effects of the optimization variables on the total fitness function to each other, a list of all solutions with their specification sets was derived in Fig. 9. The individuals with the max, median, and min fitness values over all generations were highlighted. The scales are normalized according to their defined parameter ranges as described in the caption for better visibility. Due to multiple individuals having the same fitness value but with different specifications, multiple curves are shown with the same label. A distinct impact on the overall fitness was observable for the capacity and cruise height. The two poorest individuals are on the upper end of the parameter range, whereas the best individuals are at the lower end. For cruise speed and range, it is not that clear. Here, the max, median, and min individuals are relatively close together, which could be due to the high complexity of the traffic simulation or indicate that their effect on the overall fitness is not that significant.

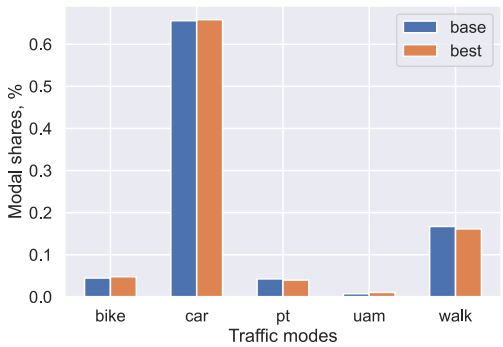


Fig. 10 Modal share comparison between the best individual from the *multi-variable optimization* and the base individual.

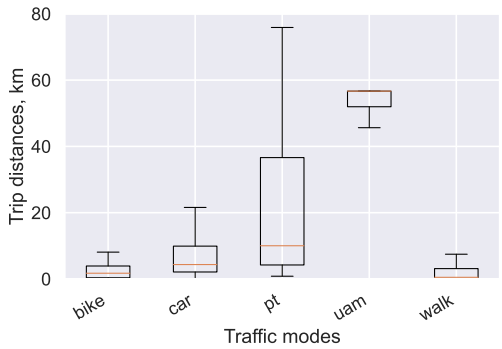


Fig. 11 Trip distance characteristics for the best individual of the *multi-variable optimization*, with whiskers for the minimum and maximum, the box indicating first and third quartile and the orange line indicating the orange median values.

After identifying the best individual from the *multi-variable optimization*, the mobility characteristics of that individual are analyzed and compared to its baseline.

First, the effect of the optimal UAM vehicle specification on other transport systems is investigated by comparing the modal shares. A slight increase in the UAM share from 0.7 % for the baseline towards 1 % for the best individual can be observed (Fig. 10). Besides that, car and bike modes are also slightly increasing, while the public transport and walk modes show a slight decrease. The modal share of agents using the optimal vehicle specification is slightly above the coverage-based estimate from before that 0.73 % of all agents have planned trips of equal or greater distance (Tab. 1). This shows that around the same share of agents that have plans with trip distances similar or larger than a corridor length are using the UAM mode and that the effects on the other transport shares are relatively small. It also supports the observation from Fig. 6, that the agents prefer to take the faster routes to shorter ones due to considering the activity schedules of the agents within the evaluation. This underlines the advantage of using an activity-based simulation approach and integrating it into the design process.

Next, the effect of the optimal vehicle configuration on the trip distances is investigated and compared with its baseline. The median UAM trip distance is 56.7 km, as shown in Fig. 11, with 96 performed trips. This is a slight increase of 4.8 km with 22 trips less than the baseline scenario. The increased distance outweighs the reduced number of trips in the overall fitness of the best individual. Together with the demand information in Tab. 1 it is apparent that the share of agents using the UAM mode is larger as the number of agents which have trips that are longer than a corridor length. This indicates that agents chose a significant trip extension for their daily activity plans despite having shorter trips, assumably because it took less time.

V. Conclusion

In the proposed work, we introduced a method for identifying optimal design concepts for Urban Air Mobility (UAM) vehicle specifications that maximize the operational profit of the fleet, based on real-world multi-agent simulations for Corsica. We first utilized public data of different vehicle design specifications through regression models to realize that. We then combined the information into multiple regression functions that reduce the number of design variables and model the operational fleet costs. Next, we implemented an optimization framework based on a Genetic Algorithm to find the optimal combination of UAM vehicle specifications with the help of multi-agent traffic simulations.

Regression models were used to ensure the feasibility of the considered vehicle configurations. This results of this study show that, compared to the base individual, the fitness could be improved by +17.9 %. The best vehicle configuration following our framework would therefore have a capacity of 1 passenger (PAX), range 187 km, cruise speed 167 km/h, and cruise height 1.3 km.

In the second part, we decoupled the vehicle parameters from each other but kept the design space from the first part. With the help of a genetic optimization scheme, an optimal individual with an improved fitness of +34.6 % compared to

the base individual could be found. The best individual, in this case, has a capacity of 1 PAX, a range of 108 km, cruise speed 176 km/h, and a cruise height 190 m.

Additionally, we investigated how a growing UAM network size would affect operational fleet costs and found out that with a larger UAM network, the profit of a fleet operator would decrease. This is because more nodes require more active vehicles to meet demand while average trip lengths decrease. Therefore, for the investigated scenario of Corsica, the smallest UAM network of 5 vertiports would operational-wise be superior to networks with 20 or 50 vertiports.

In the future, the framework will be tested for different population densities to investigate how the network size affects the UAM specification. Early results show a larger effect of network designs on vehicle specifications. Also, further aspects could be considered within the framework, e.g., cruise height constraints to avoid noise emissions in highly populated areas. This gives a first impression of the potential of the proposed method, which, through its generic character, could be applied in the future to determine optimal configurations for particular markets.

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