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Assessing noise effects of the urban air transportation system

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The paper studies air vehicle port spatial distributions within an urban area and their noise impact on population. The aim of the paper is to provide a vision of the tradeoff between the infrastructure size of the urban air transportation system (including potential revenues) and the number of negatively affected by noise produced by the system. It was conducted by modeling a number of air vehicle port distributions for various scenarios for a simulated virtual urban area. The scenarios were assessed by different metrics and the optimal solutions were determined.

I. Nomenclature

UAT	=	urban air transportation
AVP	=	air vehicle port
UAM	=	urban air mobility
CA	=	catchment area
r_1	=	reference distance from sound source
r_2	=	another distance from sound source
L_1	=	sound level at the reference distance r_1
L_2	=	sound level which is found at the distance r_2

II. Introduction

The transportation system has been demonstrating sustainable growth over the last decades. According to [1], humanity already experienced the so-called “First Transportation Revolution” with the invention of the train and the “Second Transportation Revolution” with automobiles. The “Third Transportation Revolution” (autonomous and shared mobility) is now in full swing and new technologies are rapidly accelerating and improving the process. This is finally possible because, according to [3], for the first time in history, humanity has gained enough technological knowledge to create a perfectly efficient transportation network.

An important part of the transportation system is air transport. Since the beginning of the 20th century, air transport has played an increasingly significant role in passenger mobility worldwide. Air transport connects cities, providing travel opportunities to almost anywhere in the world and, therefore, stimulating social and economic development [4] and globalization [2]. Air transport has achieved its high demand by offering swift transportation between global origins and destinations [7] at a reasonable cost in comparison to other transport modes, especially over long distances. However, due to competition with other means of transportation and in order to enhance revenue and minimize costs, the air transportation system is constantly on the lookout for ways to improve. A number of concepts which could potentially increase benefits for all stakeholders were therefore developed but never implemented due to the technological level, safety issues and lack of acceptance in society at the time. One of the concepts is urban air transportation (UAT) which has been studied by a number of commercial and research organizations [6], [8], [12] to date. Such a concept could potentially improve urban mobility by decreasing commuting times among other factors.

Since modern technologies have reached a particular level [9], [10], [11] to realize UAT systems, some, such as VOOM by A3 [5] (part of Airbus), have already been tested. Others, such as Uber Elevate [13] are about to be launched. However, implementing air transport in urban areas faces a great number of barriers, including

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community acceptance of urban air travel where pollution, especially noise and local air quality, plays a significant role. Since noise and local air quality pollution both have a greater effect around air vehicle ports (AVPs), the geographical positions of these ports have to be chosen carefully. On the one hand, the AVPs have to be easily accessible to passengers and, therefore, the ports have to be situated in populated areas. On the other hand, it may be difficult for society to accept and positively react to the presence of the AVPs in these areas and especially taking decreased revenue due to noise impact into consideration. This is why it is important to identify a tradeoff between these options and create a sustainable system where all stakeholders can profit from mutually beneficial conditions.

This study is a part of a larger study on urban air mobility (UAM). Using a system analysis approach [16], a UAM structure was defined (Fig.1). The research enabled gaps in current studies and pre-existing knowledge in that field to be identified. The whole modeling procedure in the integrated environment is aimed at answering the capacity question as to how UAM is able to increase current urban transport capacities and where UAM could help to solve those issues. Therefore, the urban area and customers are the input for the model including information such as the availability of existing UAM infrastructure (e.g. heliports), non-flying zones, customer spatial distribution, etc. All modeling blocks are interconnected and changes to one of them will trigger changes in others.

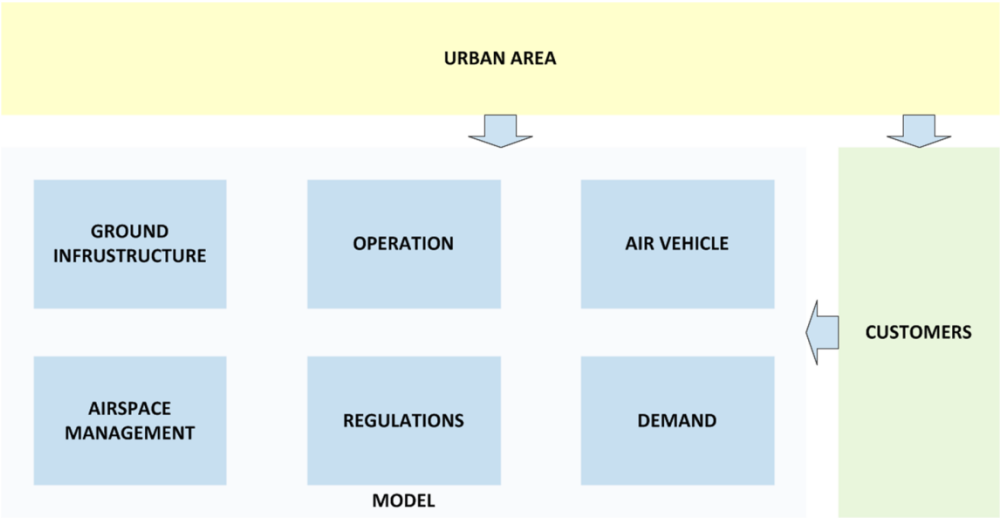


Fig.1 UAM modeling structure

After analyzing the extending version of the UAM modeling structure, one of the gaps identified was related to noise impact assessment for the AVP spatial distribution and number. Thus, the paper studies a number of AVP spatial configurations within an urban area. The aim of the paper is to model these configurations, assess their impact on noise levels and the number of people negatively affected by these effects. The modeling was conducted using a developed virtual urban area, where population, wealth and background noise levels were simulated. Then, the spatial configurations were assessed based on three scenarios and introduced metrics. The study considers three scenarios for vehicle ports placement in the urban area: “Business first” – ports are placed according to the highest passenger demand in the urban area; “Noise first” – ports are distributed in the urban area by minimum number of negatively affected inhabitants; “Combined” – ports are located in areas with the highest ratio between passenger demand and the number of negatively affected inhabitants. To choose the best spatial configuration in scenarios, three metrics were defined: passenger-kilometers (pax-km), pax-km weighed by the AVP number (pax-km-avp) and pax-km weighed by the squared AVP (pax-km-avp^2). These metrics allow the optimal AVP configurations for different scenarios to be defined, demonstrating their potential benefits and disadvantages (in this study – the number of negatively affected inhabitants). Therefore, such an approach is able to identify the optimal infrastructural solutions and assess different strategies for introducing a UAT system in the urban area.

III. Input data and assumptions

Due to the lack of real world data for urban areas and multiple challenges associated with obtaining it, a virtual urban area for this study was modeled. Taking into account the most common real urban area structures, the

emulated urban area is 7,626 km^2 (2936 sq. mi) and 16,587,000 inhabitants (Fig.2). It has two airports and a business center surrounded by residential areas with different population densities and income levels. The area does not contain AVPs and the geographical landscape is not considered. The virtual urban area was transformed into a grid with a cell granularity of 1 x 1 km. Within one cell, only one AVP can be placed in the cell center. Based on the grid, three main layers were simulated: population (Fig.3A), income (Fig.3B) and the average day-night sound levels (Fig.3C). The values for these layers were defined for every cell.

Fig.2 shows that the area has a busy, high income center, two airports and a number of major roads which are also the nosiest parts (Fig.3C). The population was divided into different categories based on inhabitant number from low density with 1,000 people per square kilometers in suburbs to 5,000 in the business center area. The income levels were simulated and assigned to the population in the area. Six categories were specified:

1. Low income
2. Middle income
3. High income
4. Passenger income in the airport 1
5. Passenger income in the airport 2
6. Business area income

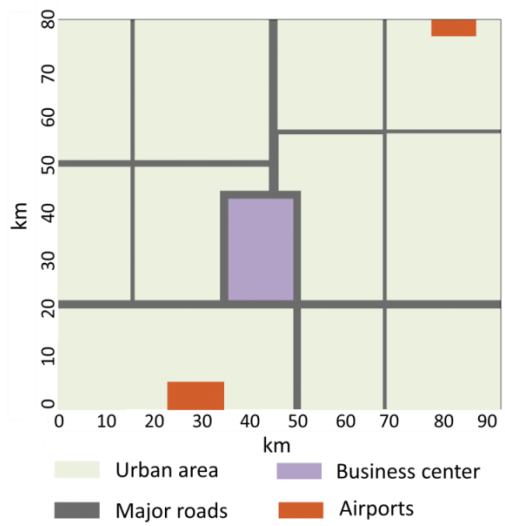
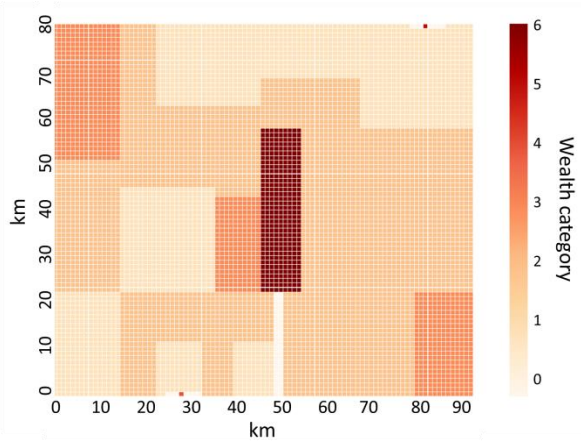


Fig.2 Virtual urban area

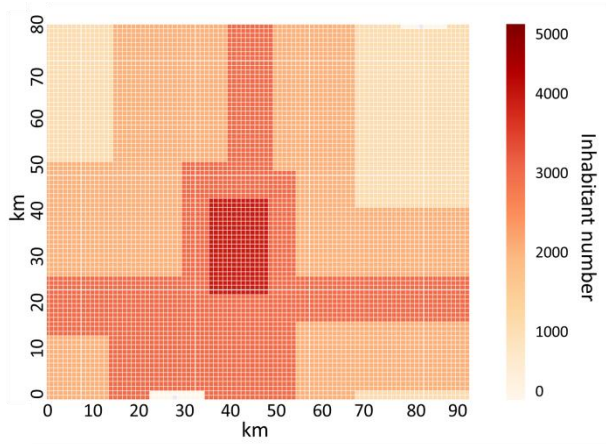
Thus, the combined simulated data of wealth and population distributions for every cell in the urban area grid is an input for the modeling. However, an additional scenario was made in order to model the AVP attractiveness in the area for inhabitants (Tab.1). The scenario includes the following parameters: passenger demand for the UAT system for one day, the average customer traveling time to AVPs and the customer speed. The passenger demand was expected to be lowest in the low income areas. The demand is gradually growing to be the highest in the business areas. It was assumed that the average traveling time to reach AVPs is longer for inhabitants in poor areas and shorter for high income people. Thus, the assumption for the average travel time to AVPs is: 0.4 hour for inhabitants from low income areas, 0.25 hour for the middle income, 0.17 for high income and the business area.

In addition, the average speed for each income category excluding airports was imitated. It was anticipated that people from poor areas have an average speed of 15 km/h – a combination of public transportation services and walking. The people from high income areas have an average speed of 30 km/h – they mainly use private transport such as cars to reach the AVPs. Inhabitants from the middle income areas have an average speed of 8 km/h – for them walking is the priority choice. It is assumed that people from business areas have a lower average speed than high income due to high building density and infrastructure congestion in the area.

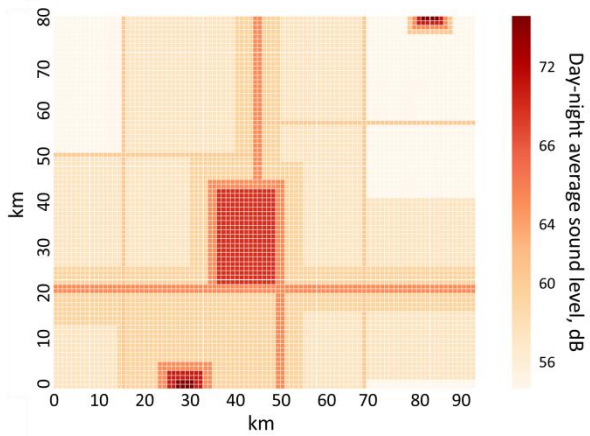
It is important to note that the air passenger demand in this study is only considered for catchment areas (CA) around AVPs in the urban area grid. This means that passenger origin-destinations between AVPs are unknown. Therefore, the study shows where the AVPs should be placed, taking into account the passenger demand in CAs, but does not simulate the network between them.



a) Heat map of wealth distribution within the virtual city



b) Heat map of population distribution within the virtual city



c) Heat map of day-night average sound distribution within the virtual city

Fig.3 Three main layers of the virtual urban area

Using the average time to AVPs and the average speed, CAs for each income category were determined. As Tab.1 demonstrates, the low income areas have the largest CAs. This means that people from those areas are able to spend more time and travel longer distances to use AVPs but the passenger demand is the lowest. The middle income category, where the catchment area is the smallest, has the opposite effect because of the low average speed. The business area shows a small catchment area of 2.55 km but it has the highest passenger demand. In addition, the airports in the urban area demonstrate the highest passenger demand such as 0.0012% and 0.0015% of the total passenger number in the airports. It is assumed that people who arrived at these airports are more likely to use the urban air mobility services than people in other areas. Thus, taking these parameters into account, the modeling approach was developed.

Tab.1 Scenario for UAT system customers by income categories

	Average time to a AVP, hours	Average speed, km/h:	AVP catchment area (CA), km	Passenger demand, % of the population:
Low income	0.4	15	6	0.000001
Middle income	0.25	8	2	0.000002
High income	0.17	30	5.1	0.000050
Business area income	0.17	15	2.55	0.001000

IV. Modelling approach

The modeling approach contains various blocks as shown in Fig. 4. The first modeling block "Calculations for the urban area" is processing data based on the virtual urban area parameters. Here, a number of additional layers could be obtained. For instance, applying the calculated CA, population and the passenger demand of each income category, the passenger number can be calculated for every cell in the urban area grid.

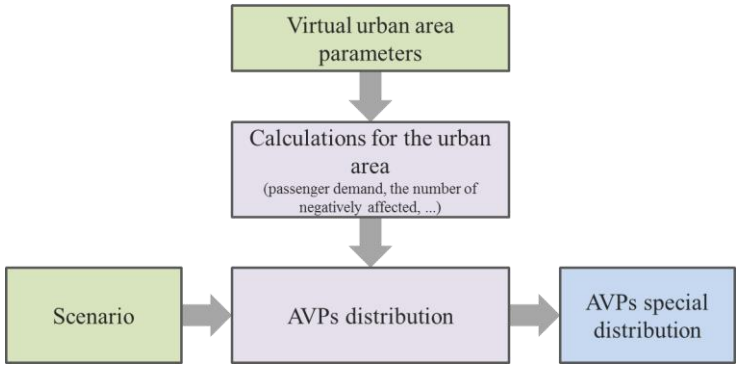


Fig.4 modeling approach

At this step, the number of negatively affected people in each cell can also be obtained. The fitting function adopted by FICON [15] (Eq.1) was used to calculate the number of the negatively affected by noise inhabitants:

$$Highly\ annoyed, \% = \frac{100}{1+e^{(11.13-0.141\,L_{dn})}} \qquad \text{Eq.1}$$

Where L_{dn} is the day-night average sound level.

In order to calculate the day-night average noise level in dB in dependence of the distance, the following formula [14] was used:

$$L_2 = L_1 - \left|20 * log\left(\frac{r_1}{r_2}\right)\right| \qquad \text{Eq.2}$$

Where r_1 - reference distance from sound source, r_2 - another distance from sound source, L_1 - sound level at the reference distance r_1, L_2 - sound level which is found at the distance r_2, and $L_{dn} = L_2$.

The calculated layers from "Calculation for urban area" and "Scenario" are the inputs for the next modeling block – "AVP distribution". "Scenario" defines a criterion for the AVP placement. For example, if the urban area has a priority for the environmentally friendly transportation system, the criteria for the AVPs placement could be a minimum number of affected inhabitants. The AVPs are placed in the urban area according to the criterion, starting from one AVP to the maximum possible AVP number in the area. It is important to admit that the modeling approach assumes that AVPs CA do not intersect i.e. that a given cell in the grid can be assigned only to one AVP. As a result, a set of various spatial configurations for different number of AVPs could be obtained. Analyzing the results, different configurations could be adopted for the UAT system. For example, it could be a configuration of a few AVPs with minimum noise impact but also fewer passengers, or it could be a system with hundreds of AVPs and a significant number of passengers, but with a high number of negatively affected inhabitants. Therefore, the proposed modeling approach will provide a number of solutions. In order to define the optimal solution for the given scenario, a special metric should be used. The metric defines the priorities and, for example, strategic planning of the urban area and identifies the optimal solution.

V. Model application and result analysis

Using the virtual urban area parameters described in Chapter III, the UAT passenger demand for each cell in the grid was calculated (Fig. 5). It can be seen that the highest passenger number is in the business center and airports. According to the assumptions, the maximum number of passengers for one cell is 75. In addition, high income areas

show noticeable passenger numbers (bottom right, and to the left from the business center). This result follows the general logic when the highest passenger number is in the areas with a high income and population density.

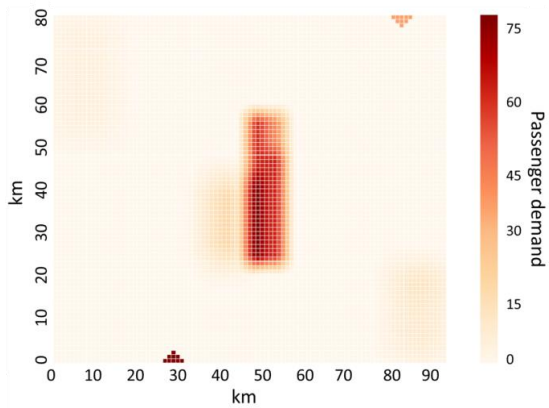


Fig.5 Passenger number for all cells in the virtual urban area

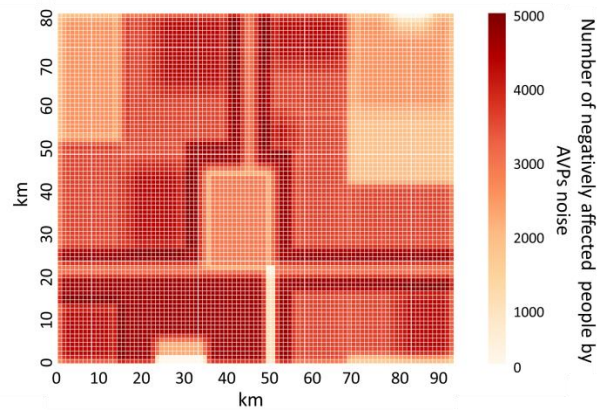


Fig.6 Number of negatively affected people by AVPs noise for all cells in the virtual urban area

In order to estimate the number of negatively affected people by noise, the background day-night average sound level was compared to noise levels produced by AVPs. If the AVP noise level is higher than the background urban noise level, it is assumed that the AVP has a negative impact in that area. In Fig.6 can be seen that a large number of inhabitants negatively affected by noise are in quiet areas with high population density.

Therefore, there are two new layers of the urban area: the passenger number and the number of negatively affected by AVP noise people calculated for each cell. These two layers and a scenario are the input for the next modeling block – AVP placement in the virtual urban area. The general aim of the modeling is to calculate sets of AVPs within the urban area based on population, income level and background noise. The modeling process was conducted for three scenarios:

1. Business first – AVPs are placed based on the highest number of passengers;
2. Noise first – AVPs are distributed by minimum negatively affected people by noise;
3. Combined – considers AVPs distribution by maximum passengers and minimum negatively affected people.

Fig.7 shows a number of AVPs and the passenger number within the urban area. Calculations were done for the three scenarios. It can be seen that the more AVPs are in the spatial configuration, the larger the passenger number. “Business first” demonstrates the highest passenger number for the given number of AVP compared to other scenarios. It is also noticeable that the “Noise first” scenario does not show a large passenger number for many AVPs. However, here it is not possible to define which AVP configuration is the best in terms of the inhabitant number affected by UAT system noise.

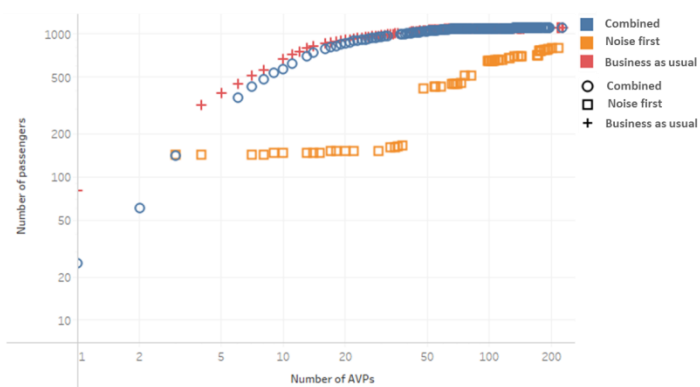


Fig.7 Passenger number in the virtual urban area for UAT system in the relation to the AVP number

Fig. 8 demonstrates the number of people negatively affected by noise from the total population and the AVP number. It can be seen that the more AVPs, the more people affected by noise. The maximum inhabitant number affected by UAT system noise is about 5% with more than 200 AVPs. The calculation shows that the noise friendly scenario has a lower number of negatively affected people for the same AVP number in other scenarios. Here, the scenario impacts are apparent: in the "Business first" scenario, AVPs are placed only taking maximum passenger demand into account, whereas in the "Noise first" scenario, ports are distributed according the minimum noise impact on the population without taking into account the passenger demand. Therefore, configurations for the "Business first" scenario require less AVPs for the same number of negatively affected people than the "Combined" and "Noise first" scenarios consequently. It again refers to the scenario logics, which have a direct influence on the AVPs' spatial distribution and the noise impact on the inhabitants of the urban area.

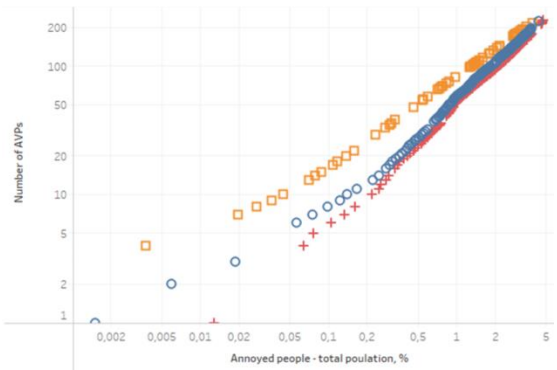


Fig.8 AVP number in the virtual urban area for the UAT system in relation to the negatively affected by noise inhabitant number

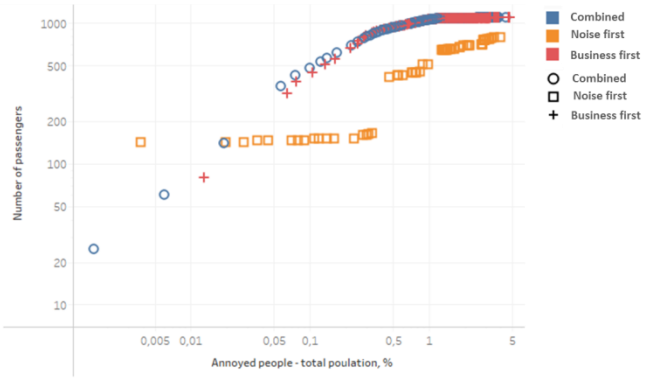


Fig.9 Passenger number in the virtual urban area for the UAT system in relation to the negatively affected by noise inhabitant number

Fig. 9 presents the number of negatively affected people and the passenger demand in the urban area. It shows that the larger the passenger number the more people are negatively affected by AVPs noise. One exceptional configuration from the "Noise first" scenario has 4 AVPs and 144 passengers and affects very few inhabitants (< 0.005%). In this case, AVPs are placed by the algorithm at airports (no noise impact since no people live) and busy road areas next to the business center area where noise level is already high and the AVP impact is negligible. By adding a larger number of AVPs, the number of highly affected people by noise is constantly increasing. However, as noise minimization is the only one assessing criteria in the "Noise first" scenario, the passenger number is not growing proportionally. Therefore, the noise friendly scenario has more negatively affected inhabitants with the same passenger demand. In addition, Fig.9 shows that the passenger number for the "Noise first" scenario increases significantly from 166 to 414 passengers when the number of negatively affected people in the urban area exceeds 0.5% and the AVP number is 38. These two effects are related to the fact that there is no more space to place AVPs in the quietest areas and the algorithm chooses other areas where the inhabitant number is large. Consequently, a single criteria optimization can only be use for initializing the system.

In order to define the optimal spatial configurations and AVPs number for scenarios, five metrics were introduced using four main parameters - the passenger number, the total distance between AVPs in kilometers, the AVP number and the number of negatively affected people and presented as follows:

1. Passenger * kilometers (pax-km) – revenue of the UAT system. The metric shows home much profit could be obtained from the given AVP configuration.
2. Passenger * kilometers / AVP number (pax-km-avp) – weighted revenue by AVPs. It demonstrates how much revenue is generated per one AVP in the system. The metric encourages a low AVP number and high revenue.
3. Passenger * kilometers / AVP number ^ 2 (pax-km-avp2) – weighted revenue by AVPs. In contrast to the previous metric, it encourages even more to have a few heliports with high revenues.
4. Passenger * kilometers / (AVP number * The number of negatively affected people) (pax-km-avp-ap)– weighted revenue by AVPs and the number of negatively affected people.
5. Passenger * kilometers / (AVP number * The number of negatively affected people) ^ 2 (pax-km-avp-ap^2) – weighted revenue by AVPs and the number of negatively affected people.

The presented metrics allow performance of various configurations in the scenarios for different strategic aims to be defined. Fig.10 shows the number of negatively affected inhabitants and pax-km.

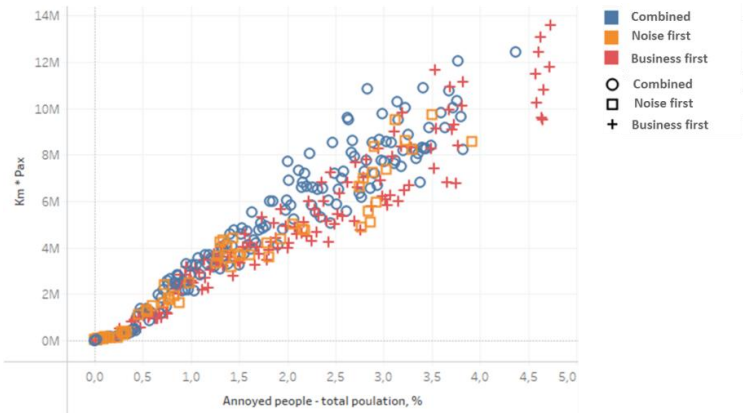
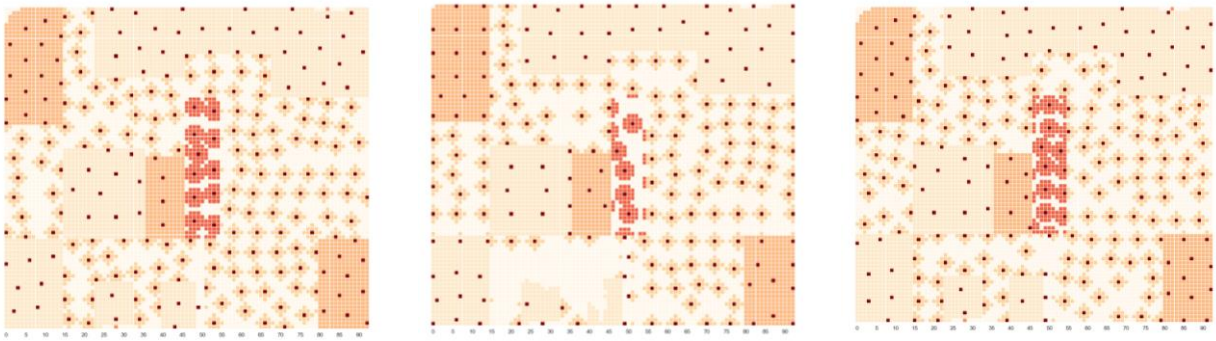


Fig.10 Spatial AVP configurations for three scenarios for pax-km and the number of negatively affected by noise inhabitants

Fig.10 shows a linear dependence between the pax-km metric and the number of negatively affected people: the higher the pax-km number the more people are negatively affected. This is because the metric gives higher values if the configuration has many AVPs i.e. there are more passengers and longer distances between AVPs. The differences in AVP distribution for different scenarios can be seen in Fig.11. In Fig.11, the darkest color indicates AVPs, CAs are colored according to the area's income level: the darker the color, the richer the area. For the "Business first" scenario (Fig.11a) the AVP configuration demonstrating the largest pax-km is the configuration with 227 AVPs, 1,101 passengers and about 4.7% of negatively affected inhabitants. In this case, AVPs are distributed almost uniformly within the urban area and placed in the cells with the highest passenger demand. The distribution for the "Noise first" scenario is different – it avoids cells with a high number of negatively affected inhabitants. In the "Noise first" scenario (Fig.11b) the largest pax-km is reached for 202 AVPs, 793 passengers and 3.5% negatively affected inhabitants. Here, the maximum pax-km value is lower than in the "Business first" scenario. The "Combined" scenario (Fig.11c) demonstrates the following results – 225 AVPs, 1,103 passengers and 4.3% negatively affected people.



a) "Business first" scenario b) "Noise first" scenario c) "Combined" scenario

Fig.11 The optimal AVPs spatial distribution for maximum passenger * kilometers

The same principle was applied for pax-km-avp (Fig.12) and pax-km-avp^2 metrics (Fig.13). For pax-km-avp were identified next optimal solutions:

- "Business first" scenario (Fig.14a): 162 AVPs, 1098 passengers, 3.5% negatively affected people.
- "Noise first" scenario (Fig.14b): 187 AVPs, 775 passengers and 3.1% negatively affected people.
- "Combined" scenario (Fig.14c): 147 AVPs, 1,098 passengers and 2.8% negatively affected people.

Considering the weighted metrics, a different dependence between the metric and the number of negatively affected people in contrast to the pax-km could be observed. The optimal solutions in this case (Fig.12) have a smaller number of negatively affected people due to a lower number of AVPs. Here, the average revenue per AVP is calculated. Therefore, the algorithm defines AVP spatial configurations with a high pax-km and a lower AVP number.

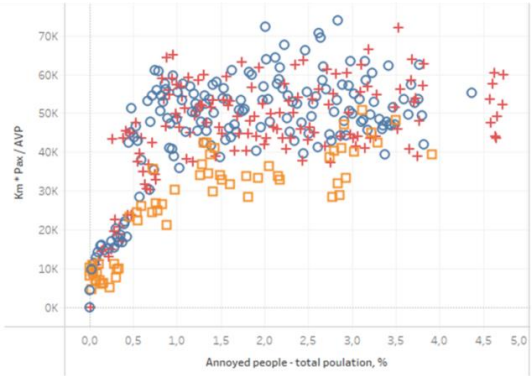


Fig.12 Spatial AVP configurations for three scenarios for the passenger * kilometers / AVP and the number of negatively affected by noise inhabitants

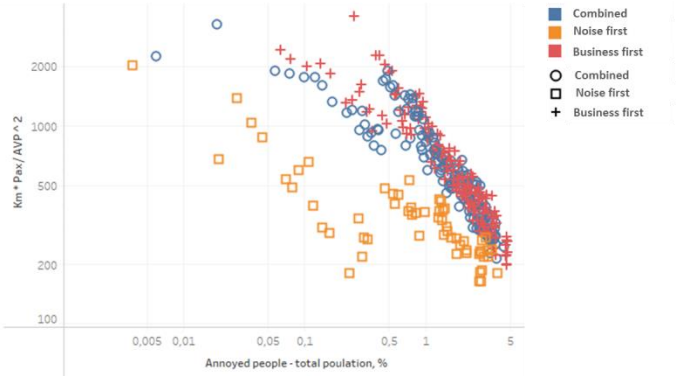
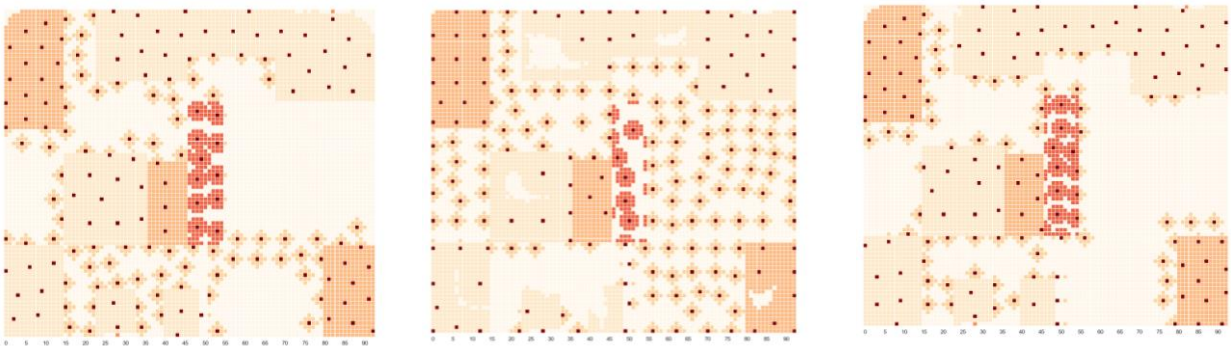
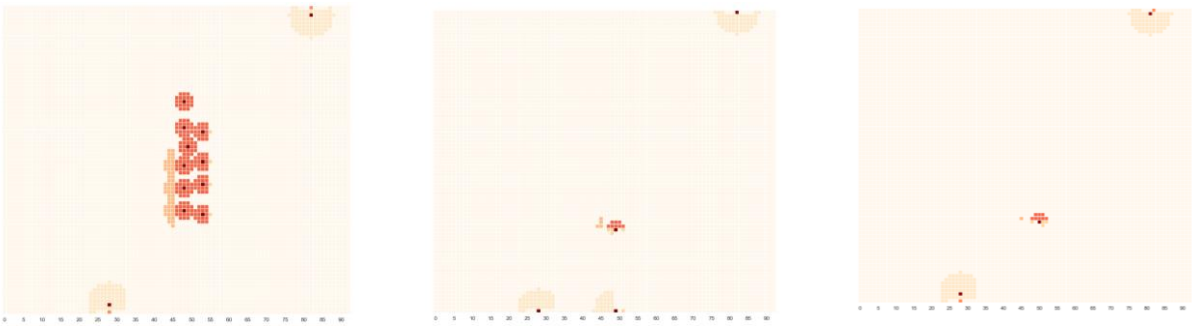


Fig.13 Spatial AVP configurations for three scenarios for the passenger * kilometers / AVP ^ 2 and the number of negatively affected by noise inhabitants



a) "Business first" scenario b) "Noise first" scenario c) "Combined" scenario

Fig.14 The optimal AVPs spatial distribution for maximum passenger * kilometers / AVP



a) "Business first" scenario b) "Noise first" scenario c) "Combined" scenario

Fig.15 The optimal AVPs spatial distribution for maximum passenger * kilometers / AVP ^ 2

For the pax-km-avp^2 (Fig. 13) the following solutions were obtained:

- "Business first" scenario (Fig.15a): 12 AVPs, 757 passengers, 0.25% negatively affected people.
- "Noise first" scenario (Fig.15b): 4 AVPs, 144 passengers and 0.004% negatively affected people.
- "Combined" scenario (Fig.15c): 3 AVPs, 141 passengers and 0.019% negatively affected people.

The algorithm gives a higher weight to configurations with a few AVPs and a large pax-km number. In other words, here is a priority for the AVP configurations which have large distances between AVPs and large passenger number. For the given virtual urban area the model placed AVPs in two airport areas (bottom left and top right – Fig.15a-c) and the business center area. This is anticipated since it is assumed that in these areas the highest demand for the UAT system exists.

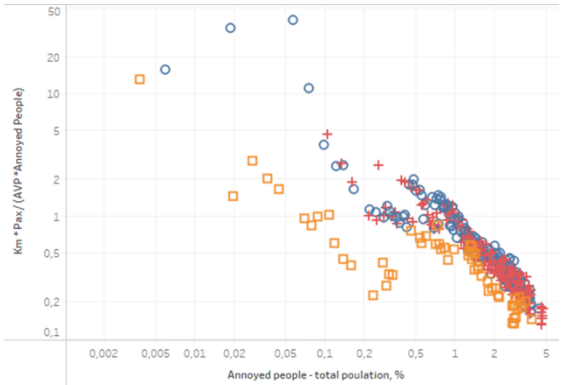


Fig.16 Spatial AVP configurations for three scenarios for the passenger * kilometers / (AVP number * The number of negatively affected people) and the number of negatively affected by noise inhabitants

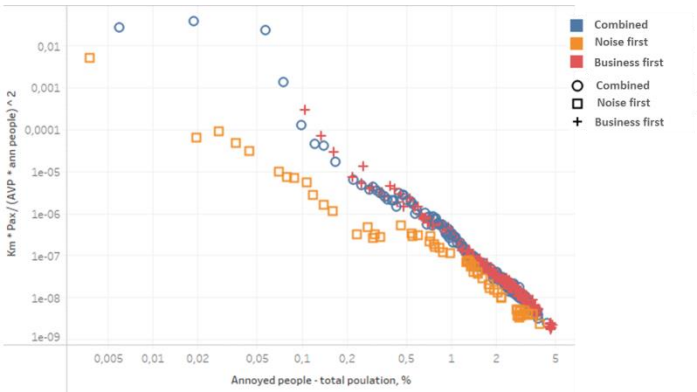


Fig.17 Spatial AVP configurations for three scenarios for the passenger * kilometers / (AVP number * The number of negatively affected people) ^2 and the number of negatively affected by noise inhabitants

For the passenger * kilometers / (AVP number * The number of negatively affected people) and the passenger * kilometers / (AVP number * The number of negatively affected people) ^2 (Fig. 16 and Fig.17) the results are the same:

- "Business first" scenario (Fig.15a): 6 AVPs, 448 passengers, 0.1% negatively affected people.
- "Noise first" scenario (Fig.15b): 4 AVPs, 144 passengers and 0.004% negatively affected people.
- "Combined" scenario (Fig.18): 6 AVPs, 360 passengers and 0.06% negatively affected people.

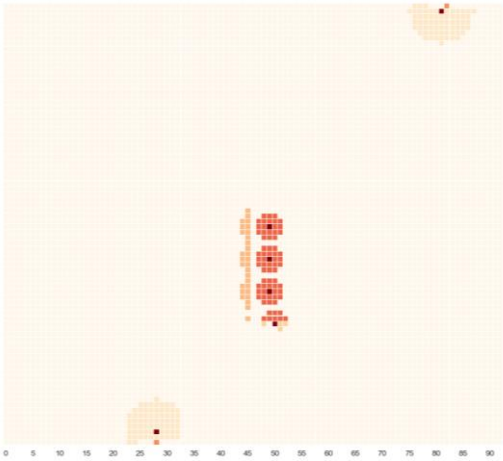


Fig.18 The optimal AVPs spatial distribution for maximum passenger * kilometers / AVP ^ 2 for "Combined" scenario

This metric shows a minor change for the "Combined" scenario: the number of AVPs increased compare to the pax-km-avp2 metric. This is because here the number of negatively affected inhabitants was taken into account in contrast to the previous metrics. In addition, it is probable that this metric describes the best AVP set for urban areas in a pragmatic way. It links the spatial positions, revenues, the AVP and negatively affected people number together in order to provide a noise friendly system for inhabitants in the area.

The detailed results of each metric for every scenario are presented in Tab.2. A tendency could be observed – the more revenues, the larger the number of AVPs and negatively affected people. Applying the weighted metrics, especially weighted by the number of negatively affected people and the AVP number, the optimal solution contains only a few AVPs and considerably low passenger numbers but with a few negatively affected inhabitants.

Tab.2. Optimal solutions details for five metrics and three scenarios

	Scenario name	Number of AVP	Passenger number	Sum of distances between AVPs, km	Total revenue, per day	Total revenue per AVP	Negatively affected inhabitants, %	Total revenue, per day per negatively affected inhabitants per AVP number
passenger * kilometers	Noise first	202	793	12,291	9,746,763	48,251	3.5	0.08
	Combined	225	1103	11,258	12,417,574	55,189	4.3	0.07
	Business first	227	1101	12,343	13,589,643	59,866	4.7	0.07
passenger * kilometers / AVP	Noise first	187	775	12,286	9,521,650	50,917	3.1	0.09
	Combined	147	1098	9,887	10,855,926	73,849	2.8	0.15
	Business first	162	1098	10,637	11,679,426	72,095	3.5	0.12
passenger * kilometers / AVP ^ 2	Noise first	4	144	225	32,400	8,100	0.004	12.2
	Combined	3	141	208	29,328	9,776	0.019	3.1
	Business first	12	757	687	520,059	43,338	0.256	1.02
passenger * kilometers / (AVP number * negatively affected people)	Noise first	4	144	225	32,400	8,100	0.004	12.2
	Combined	6	360	190	68,400	11,400	0.06	1.14
	Business first	6	448	161	72,128	12,021	0.1	0.72

Additional analysis regarding the revenue was conducted. Studying air fares from VOOM [5] in Saõ Paulo and the heliport network, the average price per kilometer, about € 9.8, was obtained. Assuming that each passenger used the system once during the day, the potential approximate revenue could be calculated. For example, for the "Combined" scenario, for the configuration with 6 AVPs, the revenue is € 670,320 and about € 1,862 per passenger or € 67 per negatively affected person. The largest amount for the revenue per negatively affected person shows the "Noise first" scenario, where the number is about € 478 for the configuration with 4 AVPs (Fig15b). However, these numbers should be considered carefully since there are a different price structures and costs for different urban areas. Nevertheless, the presented number gives a trend of the system sensibility in regards to the noise effects.

VI. Conclusion and outlook

The paper showed a specific approach for identifying an optimal AVP configuration for different criteria and scenarios. The developed modeling approach was verified on the emulated virtual urban area. Three scenarios were used to distribute AVPs within the urban area simulating preferences for the AVP placement and, thus, calculate hundreds of different AVP configurations. In order to define optimal AVP structures for each scenario, five metrics were introduced. The analysis shows that for the highest revenue, the number of heliports should be close to the maximum number that the considered area can accommodate. In this study, it was the "Business first" scenario with 225 AVPs. If it is important to minimize the number of AVPs in the area, the heavy weighted metric (pax-km-avp^2) demonstrates that, in this case, the "Business first" scenario has 12 AVPs. However, taking the number of negatively affected by noise people into account, the metric shows that the optimal solution will include 6 AVPs for the "Business first" scenario.

In this study, different scenarios were assessed and optimal solutions were found for each metric. Nevertheless, the study shows the modeling the noise effects and the assessing different metrics for virtual area and should be carefully acknowledged. Since here a general trend is shown, the situation could be different for real cities due to

other sets of input data, nonlinear scenarios and other metrics. Nevertheless, the approach presented here has potential for defining optimal positions of AVPs around the urban area. Considering additional parameters as existing transportation infrastructure, a modal split, traveling times and other information of a real urban area will significantly improve the approach. Therefore, continuing the study would provide further insights into identifying an appropriate urban area for an UAT system implementation, data collection and modeling the AVP infrastructure within the area.

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