# Catalyst fund project 1 report: Decision support tool for vertiport site selection


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## Abstract

This is the final technical report of the 'Decision support tool for vertiport site selection' (Vertiports) project, which was awarded funding through the Engage 2 KTN's first Call for catalyst funding.

# Engage 2

## Decision support tool for vertiport site selection

## Final technical report

**Engage 2 catalyst fund project**

**Coordinator: Nommon**

**Consortium partners: Bluenest**

**Thematic challenge: TC4 Integration of new entrants**

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# Engage 2

THE SESAR 3 KNOWLEDGE TRANSFER NETWORK

Engage 2

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# 1 Introduction

## 1.1 Abstract

The optimal selection of locations for take-off and landing infrastructure is key for the successful implementation of Innovative Air Mobility (IAM) services in the future. In this project, we have developed a comprehensive tool for the selection of optimal vertiport locations, using a holistic approach. The tool comprises two separate models: one dedicated to identifying vertiport sites for passenger transport, and another focused on determining the locations of lockers for last-mile drone delivery. The key contributions of this work include: (i) a review of the requirements for vertiport sites; (ii) the definition of the mathematical model used for optimisation; (iii) the implementation of the models as an executable program; (iv) the demonstration of the tool in a case study in Madrid. We demonstrate the potential of the tool by solving over 200 optimization scenarios, proving the versatility of the tool and completing a sensitivity analysis.

## 1.2 Executive summary

The rapid development of electric vertical take-off and landing (eVTOL) aircraft is driving a transformation in aviation, giving rise to the concept of Innovative Air Mobility (IAM). This emerging sector promises new opportunities in both passenger transport and last-mile delivery but also introduces significant infrastructure challenges. Currently, the lack of suitable vertiport locations remains a major bottleneck for large-scale deployment of urban air mobility systems.

To address this challenge, this project developed a decision support tool (DST) for optimising vertiport site selection. The tool will assist planners and operators in identifying the most suitable areas for vertiport networks within a given region, accounting for both passenger air mobility and last-mile logistics applications. The objectives of the project were the following:

- Reviewing the technical, regulatory, environmental, and social requirements for vertiport placement, validated through stakeholder engagement [1].
- Assessing existing methodologies for optimal location selection, including Geographical Information Systems (GIS)-based spatial analysis, optimization algorithms, and multicriteria decision-making approaches.
- Developing and implementing mathematical models tailored to passenger and logistics use cases [2].
- Building a prototype DST integrating these models with a geospatial visualisation interface for scenario analysis and stakeholder interaction [3].
- Validating the approach through a case study in Madrid, Spain, using real-world demographic, meteorological, and economic data [4].

An optimisation model was developed for each use case. The IAM passenger transport model was formulated as a Hub Location Problem (HLP) to maximize operator profit. The model estimates



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potential air-taxi demand from existing taxi demand using Mobile Network Data (MND) origin–destination matrices. The last-mile delivery Model was framed as a Maximal Covering Location Problem (MCLP) to maximize operator profit. Demand was derived from census-based population data, assuming proximity-dependent locker usage. Both models include variables such as vertiport costs, power grid connection expenses, and weather-related service availability.

The parametrisation of the models allowed testing a variety of user input combinations in the case study location, which was the province of Madrid, Spain.

- **Passenger Transport Case (Madrid):** Under conservative market adoption (maximum 3% of current taxi demand), large winged eVTOL operations were not profitable, while smaller multicopter configurations achieved positive returns. As market adoption increased, vertiport configurations remained relatively stable but diverged at very low or high adoption rates. Results show that vertiport placement is more sensitive to maximum possible demand assumptions than to pricing parameters.

- **Last-Mile Delivery Case:** The selected locations depend strongly on the influence radius (maximum walkable distance) of lockers. The selected locations showed low sensitivity to other parameters, suggesting robustness in the selected locations. Most lockers were optimally placed near dense residential zones rather than main roads.

The project successfully produced a functional prototype optimisation tool capable of supporting vertiport planning for multiple IAM applications. It integrated stakeholder-validated requirements, detailed cost and demand modeling, and geospatial visualization capabilities. The methodology provides a foundation for data-driven infrastructure planning to accelerate the deployment of urban air mobility networks. Further enhancements to the DST are recommended to increase realism and policy relevance:

- Incorporate price elasticity of demand via discrete choice models.

- Extend ground transport modeling to include additional modes (e.g., ferries, rail).

- Improve travel time estimations in geographically diverse environments.

- Refine locker influence modeling through empirical surveys.

- In the long term, integrate micro-location optimization modules to assess site-specific constraints such as obstacles, noise, and EASA-compliant safety margins.

By combining rigorous optimisation techniques with practical stakeholder input, this project advances the state of research and provides a robust analytical foundation for future IAM infrastructure development [5][6][7][8][9][10].

# 2 Overview of catalyst project

## 2.1 Operational/technical context

In recent years, the aviation sector has experienced a major shift fuelled by rapid progress in electric vertical take-off and landing (eVTOL) aircraft [11]. These innovations are paving the way for new modes of transporting both people and cargo, giving rise to the concept of Innovative Air Mobility (IAM). IAM is expected to reshape aircraft design, air traffic management (ATM), and multimodal transport systems, unlocking novel technological solutions and market opportunities. However, its success depends largely on the availability of ground infrastructure capable of supporting safe and efficient operations in dense urban settings [12]. One of the biggest obstacles is the limited availability of suitable locations for the take-off and landing hubs for these aircraft, which are commonly referred to as vertiports. Even if eVTOL vehicles were certified today, most cities would still lack the infrastructure needed to operate them at scale [13]. Numerous studies have highlighted infrastructure as the primary bottleneck to UAM deployment [12][14]. Therefore, identifying optimal vertiport locations becomes a key strategic priority for establishing an effective UAM system. Vertiport planning is fundamental, as it forms the physical backbone that supports the entire operational network [15].

In passenger transport, researchers have explored this issue through different lenses: (i) some focus on improving airport accessibility by positioning vertiports near airports to serve first- or last-mile travel [16]; (ii) others analyse urban travel behaviour to determine where air mobility could effectively complement existing transport needs [17]; and (iii) a number of studies adopt broader frameworks that incorporate factors such as demographic profiles, travel demand, and urban development strategies [18].

Last-mile delivery applications, however, involve different priorities. Efficient parcel distribution depends on proximity to logistics hubs, population density, and optimized routing. Existing approaches in this area tend to prioritize demand maximization when positioning vertiports.

Despite progress in the field, current methods for vertiport site selection still face notable shortcomings. Passenger-focused models that prioritise airport access may overlook opportunities for direct urban trips, limiting IAM's broader utility. Conversely, approaches based solely on commuting patterns may fail to account for emerging mobility needs and diverse user groups. While some studies attempt a more holistic perspective, they often omit key variables such as real-time population data, weather impacts, access constraints, infrastructure needs, and environmental effects. In the logistics domain, vertiport placement strategies are hindered by the lack of detailed delivery and traffic data, as operators tend to withhold sensitive information, ultimately leading to suboptimal decisions.

A more effective strategy for vertiport planning must integrate both operational and design requirements while leveraging advanced data analytics to make full use of available information. This project seeks to bridge these gaps.

## 2.2 Project scope and objectives

The main goal of the project is to build a decision support tool for vertiport site selection. This tool helps identify the most suitable locations for a network of vertiports within a given area, considering both passenger transport and last-mile delivery services. The specific objectives of the project are the following:

1. Conducting a comprehensive assessment of the requirements for designing different types of vertiports and the factors influencing their placement, such as airspace regulations, infrastructure availability, environmental impact, and community acceptance.

2. Performing an extensive review of diverse methodologies and algorithms utilised for optimal location determination, including, but not limited to, GIS-based spatial analysis, machine learning techniques, optimisation algorithms, and multicriteria decision-making methods.

3. Developing an optimal location model for vertiports based on the proposed design requirements and the selected algorithms.

4. Creating a prototype decision support tool that integrates the developed model with an intuitive visualisation layer for user interaction. The visualisation tool should incorporate geospatial data, scenario modelling capabilities, and user-friendly interfaces to enhance decision-making processes.

5. Assessing the effectiveness and validity of the prototype decision support tool through one or more practical case studies, involving real-world data and feedback from relevant stakeholders, to validate its accuracy, usability, and practical utility in guiding decision-making processes regarding vertiport location selection.

To limit the scope of the project, it was decided, following the completion of the literature review (objective 2), that the goal would not be to identify specific coordinates (micro location), but rather broader areas, whose size depends on the resolution of spatially distributed data. The selection of a micro location would require a detailed investigation of the site, including noise and wind measurements or simulations. Therefore, micro location selection was considered to be out of the scope of this project

## 2.3 Research carried out

The methodology of the different activities carried out in the project is presented in the following subsections.

### 2.3.1 Review of requirements for vertiport locations

A survey was conducted to identify the most relevant requirements for vertiport locations. Further details are provided in D2.1 “Analysis of requirements for vertiport location” [1]. During the first stakeholder workshop, the attendants were asked to rate the significance of each of these requirements. The list of the requirements and their ratings is presented below in Table 1. Furthermore, the table also specifies whether a requirement was implemented or not, and, if so, describes the method of implementation. The ratings are calculated using the Net Promoter Score (NPS) metric[3].

**Table 1: Requirements for vertiport locations, stakeholder ratings and implementation.**

| Requirement | Importance rating [%] | Implementation |
|---|---|---|
| REQ-001: The meteorological conditions shall allow safe operations with a sufficient frequency to justify the construction of the vertiport. | 91 | We use daily meteorological data and the drone specs to estimate the fraction of days in which a drone can operate in a year. |
| REQ-009: Local regulations for IAM flights allow for operations at the location. | 73 | We assumed more flexible regulations for the case study than current regulations. We made areas near runways prohibited. |
| REQ-019: Obstacles near vertiport shall not be a danger for operations. | 64 | Not implemented. We suggest two level optimisation for this. |
| REQ-015: The selected location shall provide sufficient space to accommodate not only the Final Approach and Take Off (FATO) area and gates, but also additional facilities (warehouse, waiting area, etc.) | 46 | Not implemented. We suggest two level optimisation for this. |
| REQ-014: The vertiport or eVTOLs do not operate on restricted areas. | 37 | The user can define these as restricted areas in the tool. |
| REQ-004: The vertiport location shall have access to GPS data of the arriving and departing eVTOLs. | 27 | The user can define these as restricted areas in the tool. |
| REQ-010: Vertiports with charging facilities shall have access to a power source of at least 1 MW. | 27 | The cost of connecting vertiport to the grid is modeled. |
| REQ-002: Fiber/ADSL communications shall be available at the vertiport location. If unavailable, alternative methods such as 4G, satellite comms or radio links could be considered, though the latter is less ideal. | 18 | Not implemented. Unnecessary in case study area. |

[3] Explained in: https://www.qualtrics.com/experience-management/customer/measure-nps/




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| Requirement | Importance rating [%] | Implementation |
|---|---|---|
| REQ-003: The vertiport's location shall allow the reception of traditional aviation frequencies within the radio spectrum. | 18 | The user can define these as restricted areas in the tool. |
| REQ-006: The vertiports shall be placed such that the UAM service has an advantage in terms of travel time and predictability compared to other transportation methods, taking into account the connectivity across transportation methods. | 9 | Not implemented. Only taxis are considered as competition in our analysis. A vertiport at the airport is always selected. |
| REQ-008: The vertiports shall be accessible from the road network or other transport network. | 9 | Not implemented. Unnecessary in case study area. |
| REQ-013: The vertiports shall not be located inside natural reserves. | 9 | Implemented. The user can define these as restricted areas in the tool. |
| REQ-017: The vertiport shall be connected to at least one other vertiport in a network. | 9 | Implemented. Travel time is also included. |
| REQ-005: The purchasing power of the users shall be taken into account when selecting locations for vertiports. | -9 | Implemented through the use of socioeconomic data in the OD matrices and population data. |
| REQ-018: The vertiport shall be only opened in certain period of the year if the demand fluctuates significantly. | -9 | Not implemented. Average daily demand in a year is used. |
| REQ-007: The price of the land to construct the vertiport shall be low enough relative to the profits to justify the investment. | -9 | Implemented. |
| REQ-012: The vertiports shall comply with the noise limits set by authorities. | -9 | Not implemented. |
| REQ-011: The vertiports shall be placed at a secure location. | -36 | Not implemented. |
| REQ-016: The cost of personnel at the vertiport location shall be low enough relative to profits to justify the investment. | -64 | Implemented (user set parameter). |



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### 2.3.2 Mathematical modelling

In parallel with the collection of requirements, a detailed literature review was conducted on optimal location problems for vertiports, lockers, and other related services. The results of this review are presented in D3.1 “Optimal vertiport location model” [2]. Based on the insights gained, it became evident that two separate models were needed: one for passenger transport and another for last-mile delivery using lockers.

#### 2.3.2.1 Last-mile delivery

The last-mile delivery service is assumed to function as represented in Figure 1. The drone operates from a warehouse where parcels are stored, collect the parcels, and deliver them to designated lockers. Users can then retrieve their parcels once they become available at the locker. It is further assumed that the service is used exclusively by residents living within the locker’s area of influence (i.e., within a predefined influence radius).

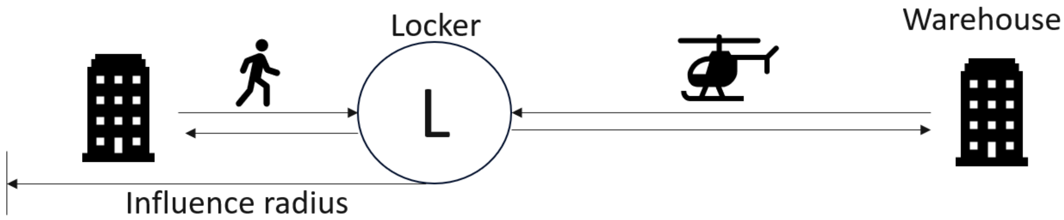


**Figure 1: Diagram of the assumed last-mile delivery service operation**

The demand of a locker is only affected by another locker if they are close to each other (within the influence radius), as some customers would switch between them. To model the associated costs and demand, the following assumptions are made:

- **User profile:** Employed individuals are more likely to use lockers instead of home delivery, therefore they are used to estimate the potential demand [19].
- **Distance decay:** The likelihood of a customer using a locker decreases linearly with distance from their home (see Figure 2). The probability reaches zero at the influence radius, also referred to as the “maximum walkable distance”, $d_{mw}$.
- **Market size:** The total available market is assumed to be the number of rapid deliveries by Amazon (0.02 per day per occupied person).

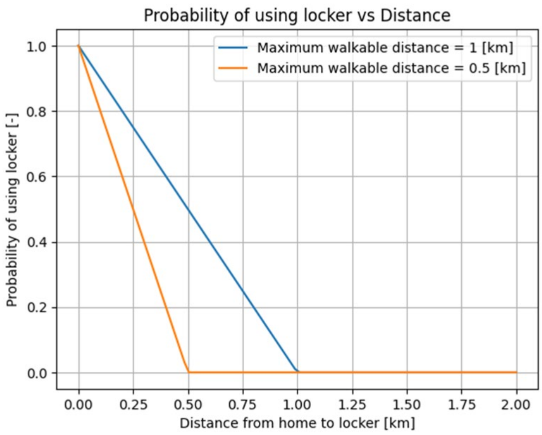


**Figure 2: Probability of a potential customer using a locker as a function of the straight line distance from the home to the locker**

Since the aim is to maximise the captured demand / revenue with a limited budget, the problem is framed as a Maximal Covering Location Problem (MCLP) from the perspective of the vertiport operator [20], with the objective of maximizing the profit. The resulting objective function is presented below:

$$max \sum_{k \in N} (f k_{max} w_k P_k D_k - L_k)\, y_k \quad (1)$$

Where:

- $D_k$[Deliveries / Day]: Potential demand at location $k$ (based on influence radius).
- $k_{max}$ [-]: Assumed maximum possible market penetration.
- $P_k$ [-]: Fraction of the population within the influence radius that would be willing to travel to the locker for a parcel (based on the function in Figure 2).
- $f$ [EUR/ Delivery]: commission per delivery.

Finally, $L_k$ are the average costs per day for location $k$. These are modelled as shown below:

$$L_k = MAI + \frac{1}{T_a}(INF + F_k S_v) \quad (2)$$

Where:

- MAI [EUR/Day]: Locker maintenance cost.
- INF [EUR]: Locker construction cost.
- $F_k$ [EUR/m$^2$]: Approximated floor cost at the location.
- $S_v$ [m$^2$]: Surface area needed for the locker.
- $T_a$[Days]: Payback time, based on the expected lifetime of the infrastructure.

In terms of constraints, there are constraints on the maximum number of lockers, the maximum number of daily deliveries per locker, and the minimum distance between two lockers.

#### 2.3.2.2 IAM passenger transport

The passenger transport IAM service is assumed to operate as shown in Figure 3. The passenger takes a personal car, company car or taxi to the access vertiport. From there, an eVTOL takes the passenger to the egress vertiport, from which they continue their journey to the final destination.

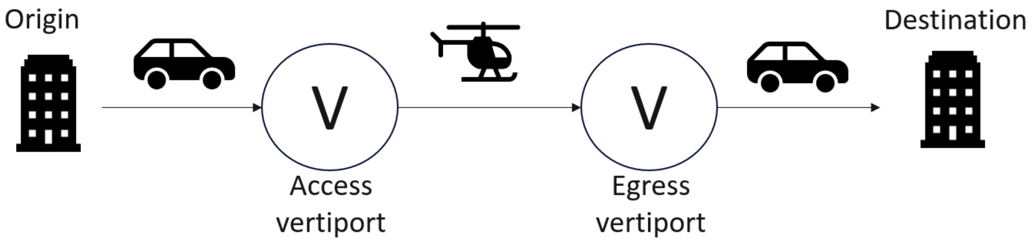


**Figure 3: Diagram of the assumed IAM passenger transport service operation**

The following assumptions are made to model the costs and demand associated with this service:

- **Flexible (On-Demand) network:** The air taxi service operates without predefined routes. Passengers are free to travel between any pair of vertiports.
- **Demand based on existing taxi usage:** Potential air taxi demand is estimated from current usage of taxis and other private road transport. Future eVTOL ridership is projected using a market penetration model, assuming that a share of current ground taxi trips will shift to air taxis once the service becomes available.
- **Inelastic demand:** Early adopters are expected to come from higher-income groups with low price sensitivity. For these users, the benefits of eVTOLs, such as time savings and convenience, are likely to outweigh the higher cost compared to conventional modes.
- **Discrete demand points:** Travel demand is aggregated into distinct spatial nodes, which act as origin and destination points in the model.
- **Daily average demand:** The optimisation is based on total daily demand, without accounting for hourly or intraday fluctuations.
- **Minimum trip length requirement:** Only trips exceeding a certain distance are considered viable for urban air mobility, assuming passengers will not choose air taxis for very short journeys.
- **Free-Route airspace with No-Fly zones:** eVTOLs are assumed to fly along direct point-to-point paths unless restricted airspace is encountered. In such cases, the vehicle follows the shortest detour around the restricted zone.

To estimate the IAM demand from taxi demand, a simplified choice model inspired by Uber Elevate [13] is used. The probability of a passenger using IAM over a conventional taxi is modelled using a sigmoid function, as shown in Figure 4. This function is adjusted through a user parameter, referred to as Travel Time Ratio Parameter (TTRP).

Given the multimodal nature of the problem, and following previous studies, the optimisation is formulated as a **Hub Location Problem** [21][22][23][24]. The objective function, presented below, aims to maximize the revenue of the vertiport network operator:

$$max \sum_{p \in P} \sum_{k \in N} \sum_{d \in N} f^{p}{}_{A,kd} w_{kd} D^p P^p{}_{A,kd} x^p{}_{kd} - \sum_{k \in N} V_k y_k + (H_k - V_k) z_k \quad (3)$$

Where:

- $D^p$[trips/day]: average daily number of potential IAM trips between OD pair *p*.
- $P^p{}_{A,kd}$ [-]: probability of a potential IAM customer using IAM through vertiports *k* and *d* instead of taxi with eVTOL *A*.
- $w_{kd}$ [-]: fraction of days in year where the route can be operated due to favourable meteorological conditions.
- $f^p{}_{A,kd}$ [EUR/trip]: earnings per trip based on a commission per passenger, another per operation, and another per[kWh] of electricity used for charging.

The costs for a vertiport $V_k$ or for a vertihub $H_k$, are computed as follows:

$$V_k = n_{emp} SAL + MAI + \frac{1}{T_a}(CON_k + INF + F_k S_v) \quad (4)$$

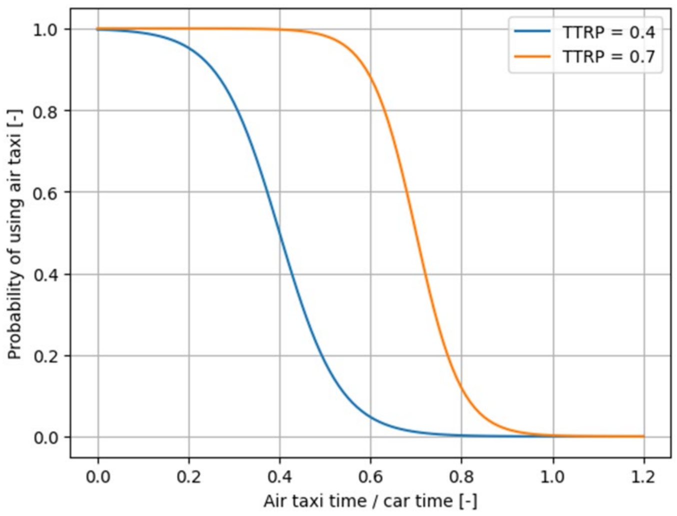


**Figure 4: Probability of using air taxi as a function of the ratio of the travel time by air taxi over travel time by car**

Where:

- $n_{emp}$ [-]: number of employees.
- *SAL* [EUR/día]: employee salaries.
- $CON_k$[-]: connection cost to the power grid, including any potential substation expansions.
- The remaining terms have the same meaning as for lockers, but their values are adjusted.
- *MAI*, *INF* y $n_{emp}$ have different values for vertihubs.

The model includes several constraints. First, the total number of vertiports is fixed to a user-defined parameter, $n_{vert}$,. Second, demand can only be assigned to routes that connect through constructed vertiports. Finally, the maximum operational capacity of each vertiport, expressed in operations per day, must not be exceeded. Vertihubs are assumed to have higher capacity than standard vertiports; however, their construction and operational costs are also greater.

The following formula for the earnings per trip is assumed:

$$f^{p}{}_{A,kd} = c_{prices}\left(\frac{f_{op}}{n_{A,pass}} + f_{pass} + \frac{f_e E^{p}{}_{A,kd}}{n_{A,pass}}\right) \quad (5)$$

Where $f_{op}$ is the commission per operation, $f_{pass}$ is the commission per passenger and $f_e$ is a commission per kWh of electricity. $n_{A,pass}$ is the number of passengers per drone, $E^p{}_{kd}$ is the energy consumed in the IAM trip and $c_{prices}$ is a factor to modify all components proportionally.

### 2.3.3 Case studies

Both the passenger transport and last-mile delivery case studies were conducted in the same geographical area: the province of Madrid, Spain. However, two key differences can be identified:

- **Spatial resolution of the demand data:** The demand data were obtained from different sources depending on the case study. For the last-mile delivery case, population data are provided at the census tract level, which in densely populated areas can have maximum dimensions of around 100 m. In contrast, for the passenger transport case, the OD matrices are defined over spatial zones whose maximum dimension is rarely below 1 km.
- **Study area definition:** In the last-mile delivery case, the study area depends on the location of the warehouse and the operational range of the drones, as lockers outside this range cannot be reached by the service. For the passenger transport case, the study area corresponds to a rectangular region in the ETRS89 projection, whose vertices are defined by the administrative boundaries of the province.

### 2.3.4 Model implementation

This section outlines the different data pipelines which we implemented as part of the DST. These modules process raw data from a variety of sources to obtain intermediate results and models that are needed as inputs for the optimisation models presented in Sections 2.3.1 and 2.3.2.

#### 2.3.4.1 Last-mile delivery

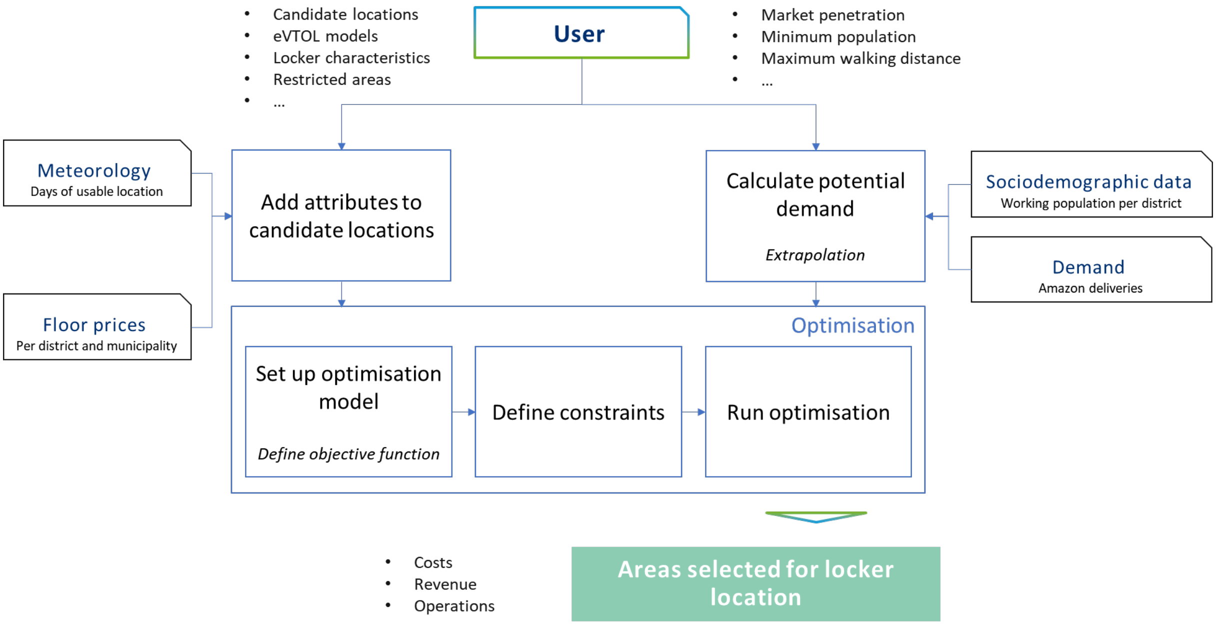


**Figure 5: Functional block diagram of the last-mile delivery case**

##### 2.3.4.1.1 Potential demand estimation from population data

To estimate the spatial distribution of potential demand, Dk, as defined in Equation (1), data on the employed population per census tract provided by the Instituto Nacional de Estadística (INE) [25] is used. The population is assumed to be uniformly distributed in each census tract. The demand is then discretised onto a uniform grid of user-defined resolution (i.e.: 100 x 100 [m]), assigning the population to the centre of the grid-cell based on the population density and cell area.

To estimate the average number of daily deliveries, a factor derived from Amazon data is assumed, stating that approximately 160 million fast deliveries were made in Spain in 2024 [26]. This corresponds to roughly 0.02 deliveries per day per occupied person. This factor is applied to the population assigned to each cell, resulting in a spatial distribution of potential delivery demand. Based on this distribution, and $d_{mw}$, it is possible to calculate the demand associated to each locker $k$, $D_k$. The method used for this task is explained in detail in D4.1 [3].

##### 2.3.4.1.2 Candidate locations attributes

The following modules describe the main data processing steps used to generate attributes associated with each candidate location. In addition to these processed datasets, raw input variables (e.g.

maintenance costs, infrastructure costs, etc.) are directly linked to candidate locations but are not detailed here, as they require no additional processing.

**Cost of urban floor**

The cost of purchasing urban land for locker construction, Fk, as defined in Equation (2), was estimated using a weighted combination of two data sources: parcel prices from the Spanish Ministry of Housing [27] and apartment prices from Idealista [28]. The weighting depends on the population density of each district or municipality, with higher densities giving more weight to apartment prices.

**Weather constraints**

Weather-related constraints on drone operation were modeled using meteorological data from 2022 to 2024, collected from Spain's national weather agency (AEMET) [29] and complemented with visibility data from the Automated Surface Observing System (ASOS) [30]. For each day and station, variables such as temperature, wind speed, precipitation, and visibility were compared with the operational limits of the aircraft to determine whether flight conditions were suitable. The fraction of days suitable for flight was then calculated for each weather station, spatially interpolated across the study area, and assigned to each locker. This allows the estimation of the number of days a locker is available, wk, which is present in Equation (1).

#### 2.3.4.1.3 Optimisation

The optimisation engine was implemented in python using a greedy algorithm that selects locker locations sequentially. At each iteration, the algorithm identifies the location that provides the highest increment in profit for the whole network. The process follows these main steps:

1. Location costs computation: For each candidate location, the associated costs (construction, floor, maintenance, etc.) are computed.
2. Demand discretisation: The spatially distributed demand (originally represented as polygons in a data frame) is converted into a uniform grid, whose cell size is specified by the user.
3. Iterative selection loop: Locations are selected iteratively until no profitable locations are left or the maximum number of locations has been reached. At each iteration, the additional demand captured by introducing a new locker is estimated, and the location yielding the highest marginal profit is chosen.

### 2.3.4.2 IAM passenger transport

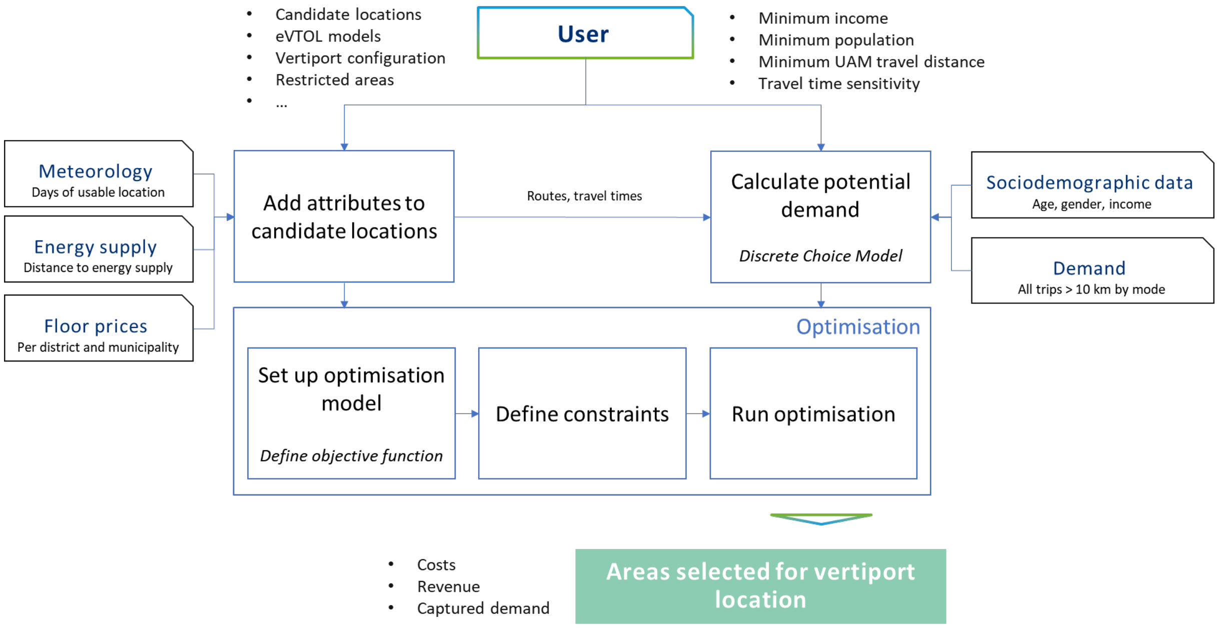


**Figure 6: Functional block diagram of the passenger vertiport case**

#### 2.3.4.2.1 Potential demand estimation from MND OD Matrices

To estimate potential demand, $D^p$ , as defined in Equation (3), daily Origin–Destination (OD) matrices derived from Mobile Network Data (MND) were used. These matrices, provided by Nommon for the Spanish Ministry of Transport, contain trip information at the district level, with spatial resolutions ranging from approximately one kilometre in urban areas to ten kilometres in rural zones [31]. Four representative weeks of data were analysed, one from each quarter of 2024, excluding trips shorter than 10 [km]. Each OD entry includes attributes such as sex, income, and trip frequency, although the transport mode is not specified.

To infer the share of taxi trips within this dataset, a logistic regression model was trained using data from the 2018 Madrid Mobility Survey [32]. The model predicts the probability of a trip being made by taxi based on three features: the travel distance, the per-capita income of the passenger's district of residence (or the average income between origin and destination if unavailable), and whether the trip is infrequent. The logistic model was trained using trips longer than 5 km with the LBFGS solver for 2000 iterations, achieving a test-set log loss of 0.034. Once trained, it was applied to the OD matrices to estimate the number of taxi trips across all OD pairs.

Recognising that air-taxi adoption is likely to depend on income, a market penetration model was introduced. Higher-income passengers were assumed to have a higher probability of using air taxis due to their higher willingness to pay. To represent this, a parameter kmax between 0 and 1 was defined to cap the maximum achievable market share of air taxis within the taxi market. This parameter varies depending on income level, keeping the same proportional differences between income groups observed for taxis among all transport modes. A system of linear equations ensures consistency across income segments, after which OD entries with the same OD pair are aggregated to compute the total number of potential IAM passengers per OD pair, Dp.

#### 2.3.4.2.2 Candidate locations and routes attributes

The candidate locations and the routes between them were enriched with additional information related to their surrounding context (e.g., weather, floor costs, connection costs) and network connections (e.g., IAM travel time, car travel time). The main data processing modules used to compute these attributes are described below. Raw input data directly linked to candidate locations (such as maintenance costs, number of gates, or number of gates equipped with chargers) are not included here, as they do not require further processing.

**IAM passenger transport distance and travel time estimation**

For IAM travel time estimation, a free-route airspace assumption was adopted, allowing aircraft to fly directly between vertiports while avoiding restricted zones. Restricted areas were modeled as polygons, from which a graph was constructed using polygon vertices as nodes and valid straight-line connections as edges. Access and egress vertiports were added as extra nodes, with edges drawn only if they did not intersect restricted areas. The shortest viable distance between vertiports was then determined using the A* algorithm [33], with edge weights equal to Euclidean distances. The total air travel time is then estimated assuming a constant speed equal to the cruise speed of the drone, supplemented by a fixed time penalty accounting for boarding, disembarking, take-off, and landing operations.

**Car travel time estimation**

Car travel times were estimated using a surrogate model based on the Mapbox navigation API [34], which provides driving times between various origin–destination pairs while accounting for road networks, speed limits, and typical traffic patterns. The collected dataset was used to fit a symbolic regression model that relates travel time to three key variables: the Euclidean distance between the origin and destination ($d$), and the distances from both the origin ($r_1$) and destination ($r_2$) to Madrid's traffic center, defined as the location with the highest population density within a 5 [km] radius.

The resulting regression function for Madrid, detailed in [10], achieved a root mean squared error of 8.3 minutes and a mean percentage error of 14 %. The hyperbolic tangent term captures the nonlinear increase in travel time with distance, which reflects congestion and urban density effects. Finally, based on the travel time, it was estimated the fraction of the trip that was taken in (i) urban roads, (ii) conventional roads and (iii) highways. Then, using speed data from mapbox [34] and the ministry of transportation [35], the time difference between the 50th and the 90th percentile of travel times between two locations was estimated.

Finally, the ratio between car and IAM travel times was used to estimate the probability of choosing air taxi transport for each route, $P^{p}_{A,kd,}$ as shown in Figure 4.

**Cost of connection to electricity grid**

The cost of connecting each vertiport to the electricity grid, $CON_k$, was modelled using an approach developed by Cintrano and Toutouh [36] for car charging stations. The term is present in equation (4). The connection cost depends linearly on the distance between a vertiport and the nearest electrical substation, considering whether the substation requires an upgrade due to limited spare capacity (less than 1[MW]).

**Cost of urban floor**

The cost of purchasing the floor for the construction of vertiports is calculated in the same fashion as for lockers. The main difference lies in the calculation of the area for the vertiports, $S_v$, which has been performed with the MAIA Vertiport Capacity and Area tool (http://vsctool.sf.bg.ac.rs/index.html). The calculation of area and capacity depends on the following user inputs:

- Vertiport Layout
- eVTOL maximum wingspan
- eVTOL seats
- Number of gates

**Weather constraints**

The weather constraint term, $w_{kd}$ , defined in equation (3), was calculated using the same method as in the locker use case, but considering the operational limitations of passenger eVTOLs rather than delivery drones. In this case, the effective operational availability for each route was defined as the minimum value between its access and egress vertiports.

#### 2.3.4.2.3 Optimisation

The optimisation engine for this use case was implemented using the Pyomo library, which provides a flexible framework for defining and solving mathematical programming problems. The implementation comprises the following components:

- Definition of the decision variables
- Definition of the constraints
- Definition of the objective function
- Solver selection.

Pyomo serves as an interface to optimisation solvers implemented in other programming languages. In this study, the SCIP solver was used, an open-source, heuristic Mixed-Integer Linear Programming (MILP) solver particularly suited to combinatorial optimisation problems.

### 2.3.5 Decision Support Tool development

As a final step, a **Decision Support Tool (DST)** was developed to provide an interactive environment for exploring and interpreting the results generated by the models. The tool offers a suite of dynamic and geospatial visualisation tools, including maps, charts, tables, and plots, allowing users to intuitively analyse spatial distributions, performance metrics, and key indicators. Users can switch between layers, select attributes to display, and use tooltips to access detailed contextual information directly on the map.

The map tab includes the map, the total revenue indicator and a dropdown menu that allows users to select the variable displayed across the geographical areas. The user can select between total population, population density and income. Candidate locations are shown as blue dots in the map, while the selected locations are highlighted in red.

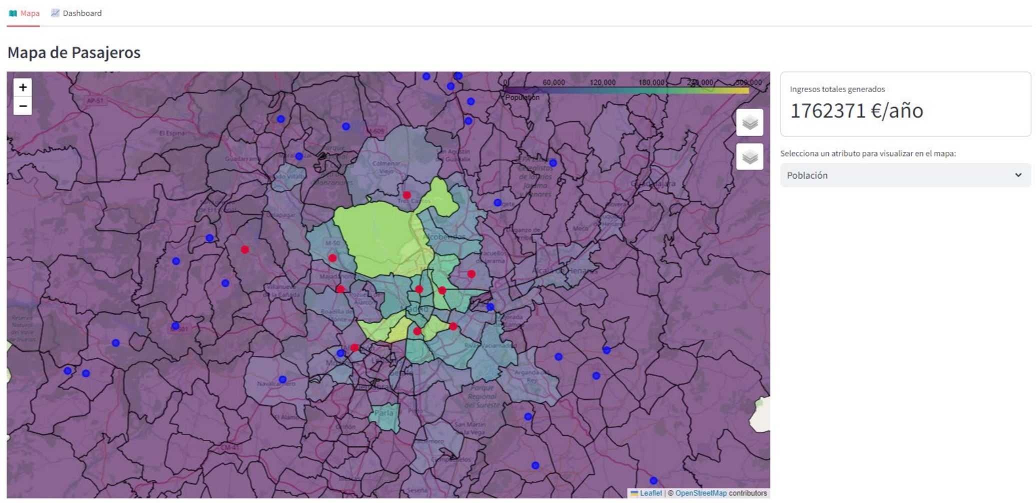


**Figure 7: Visualisation page - Map tab**

Comparative analyses are supported through bar and pie charts that illustrate differences in performance, costs, and operational factors across selected locations or scenarios.

The visual outputs can be exported for reporting or further analysis, ensuring that insights derived from the models are both accessible and communicable. Tailored visualisation features are provided for passenger and last-mile delivery operations, adapting the displayed content and metrics to the specific nature of each study.


**Figure 8: Visualisation page - Dashboard tab**



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## 2.4 Results

### 2.4.1 Last-mile delivery results

The test matrix considered in the last-mile delivery case study is presented in Table 2. A factorial experiment design was used, therefore testing all possible combinations of the independent variables. All other model variables were kept constant throughout the experiments.

**Table 2: Test matrix for the sensitivity analysis of the vertiport optimization tool for last-mile delivery**

| Variable | Values |
|---|---|
| $d_{mw}$[km] | 0.5, 1 |
| $k_{max}$ [%] | 1, 3, 6, 10, 20 |
| $f$ [EUR] | 1, 1.5, 2, 3.5, 5 |

Except the scenarios with $k_{max}$ = 1 [%] and $f$ < 3.5 [EUR], the rest are all profitable for the locker operator. We plot the selected locations for the two scenarios with $k_{max}$ = 6 [%] and $f$ = 2 [EUR] in Figure 9.

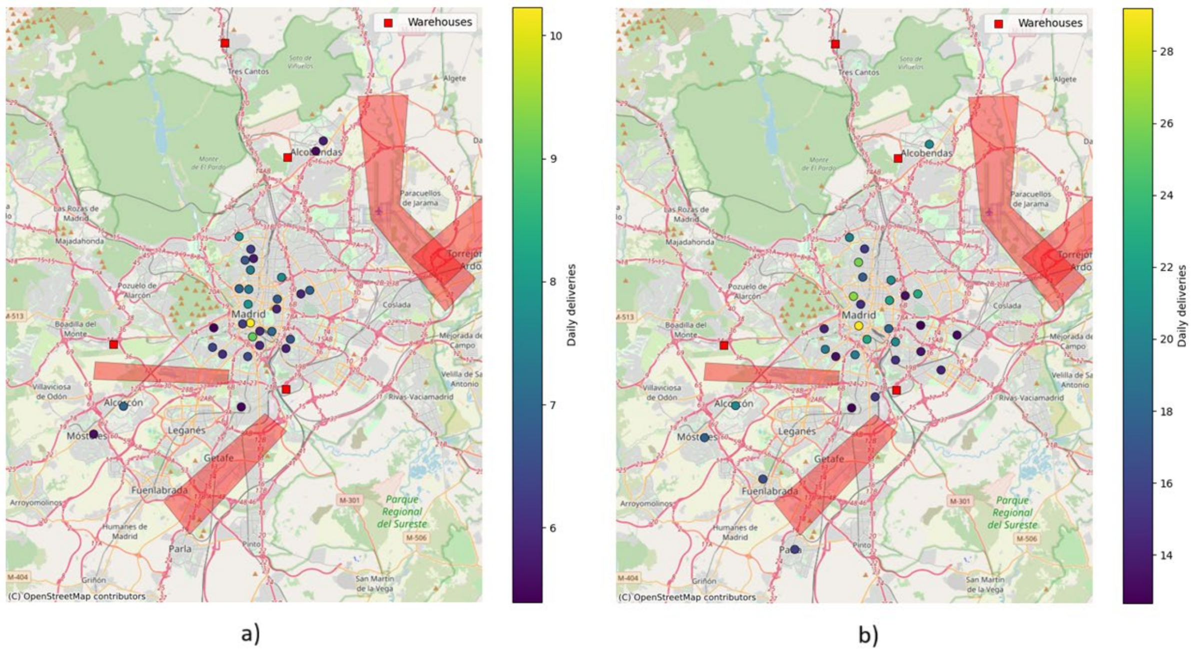


**Figure 9: Selected locations and daily deliveries per location for the last-mile scenarios with kmax = 6 [%] and f = 2 [EUR] for a)dmw = 0.5 [km] and b) dmw = 1 [km]. The color of the location markers indicate the number of daily deliveries.**

As can be seen in Figure 9, most locations are centred around the densely populated city centre. Furthermore, the selected locations are generally noticeably separated from major roads, which are coloured pink in the maps. This is explained by the lower population density of the census tracts that include large road corridors, which aligns with the assumption that customers are more likely to use lockers near their homes.

When the maximum walkable distance, $d_{mw}$, increases, the selected lockers become more spatially dispersed, with additional sites appearing in the outer districts of Madrid and other surrounding cities. The reason behind this is that, with a larger $d_{mw}$, the lockers have to be separated further to avoid redundancies, i.e., situations where two lockers compete for the same customers, reducing profitability. Such competition would not arise if lockers operated near their maximum capacity. However, in this study, a capacity of 70 deliveries per day per locker was assumed. With this capacity only certain lockers become saturated, and it only occurs in scenarios with $k_{max}$ = 20 [%], $d_{mw}$= 1 [km].

For the sensitivity analysis, a metric measuring the similarity between two sets of locations was created. The more stable the selected locations are to changes in user parameters, the more robust the results can be considered, minimising errors due to mistakes in the user inputs. To do this, a minimum-cost assignment problem that minimises the total distance between two sets of selected locations was solved. One set corresponds to a reference scenario $R = \{r_1, r_2, \ldots\}$, while the other set represents an alternative scenario $O = \{o_1, o_2, \ldots\}$. Then the matching pairs $\mathcal{M}$ that minimise the average distance between corresponding locations were identified:

$$d_{mean} = \frac{1}{n_{vert}} \sum_{(i,j)\in\mathcal{M}} \mathrm{dist}(r_i, o_j)$$

where dist() denotes the Euclidean distance between points (in kilometres). If the two sets of locations are identical, $d_{mean} = 0$; as their spatial differences increase, $d_{mean}$ becomes larger. This has been plotted for the 50 scenarios in Figure 10. The selected locations seem to have very little sensitivity to the assumed $k_{max}$ and commission, which is a positive result. Nonetheless, $d_{mw}$ affects the selected locations quite significantly, as could also be seen in Figure 10.

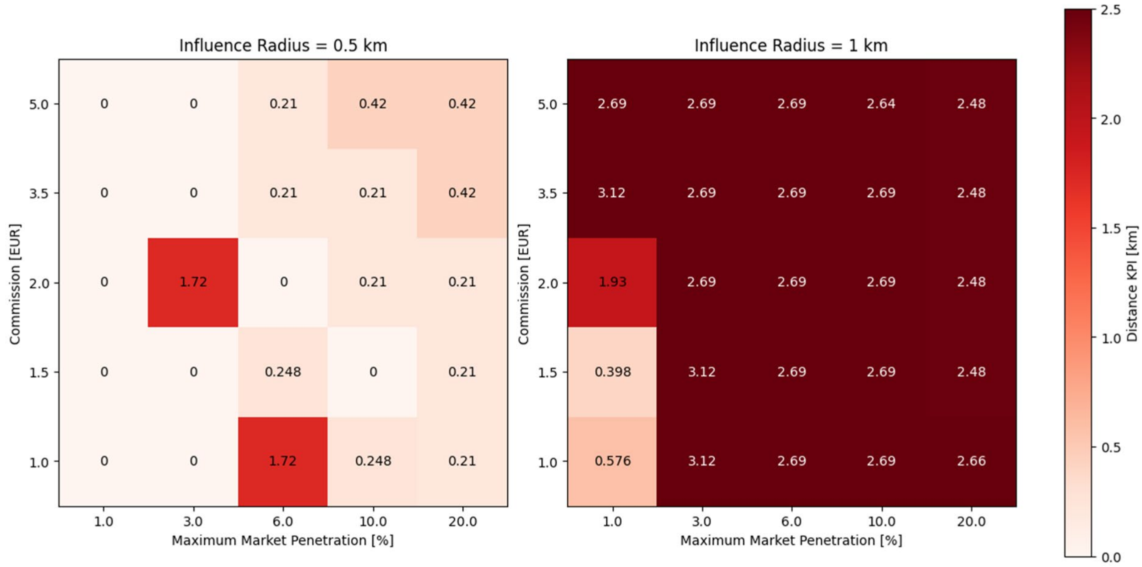


**Figure 10: Heatmap showing the dmean values for every simulated last-mile scenario. On the left are the cases with dmw = 0.5 and on the right the cases with dmw = 1.**

### 2.4.2 IAM passenger transport results

We consider the test matrix shown in Table 3. A factorial experiment design was also applied for the IAM passenger transport case study. All other model variables were kept constant, as detailed in[4][10].

The specifications of the eVTOLs are based on real aircraft, although their names have been modified. These aircraft influence the optimisation results not only through their technical specifications but also through the design characteristics of the corresponding vertiports and vertihubs. The key differences are as follows: the multicopter has a cruise speed of 100 [km/h] and a maximum dimension of 5 [m], while the winged eVTOL reaches a cruise speed of 200 [km/h] with a maximum dimension of 12 [m]. This means that a larger and more costly vertiport is needed for the Winged eVTOL. We also consider 3 specific user adoption scenarios fixing $n_{vert}$ = 10, and TTRP = 0.7:

1. Early scenario (Multicopter and Winged): $k_{max}$ = 3 [%], $c_{prices}$ = 1.5 [-]
2. Baseline scenario (Winged): $k_{max}$ = 6 [%], $c_{prices}$ = 1.5 [-]
3. Optimistic future scenario (Winged): $k_{max}$ = 10 [%], $c_{prices}$ = 2 [-]

The summary of the optimisation results for these selected scenarios is presented in Table 4. As can be observed, the higher income per passenger combined with the lower costs for multicopter, make it more profitable for more conservative scenarios. Nonetheless, winged attracts a larger number of customers due to its lower travel time between vertiports. The map with the candidate and selected locations for each scenario are plotted in Figure 11.

**Table 3: Test matrix for the sensitivity analysis of the vertiport optimization tool for IAM passenger transportation**

| Variable | Values |
|---|---|
| eVTOL | Multicopter, Winged eVTOL |
| $n_{vert}$ [-] | 5,10 |
| TTRP[-] | 0.4, 0.7 |
| $k_{max}$ [%] | 1, 3, 6, 10, 20 |
| $c_{prices}$ [-] | 0.5, 1, 1.5, 2, 4 |

**Table 4: Summarized results of the 4 selected scenarios**

| Scenario | Profit [EUR/day] | Income [EUR/day] | Costs [EUR/day] | Passengers [-] | Income per passenger [EUR] |
|---|---|---|---|---|---|
| 1-Multi | 1410 | 11600 | 10200 | 84 | 138 |
| 1-Winged | -6420 | 8480 | 14900 | 112 | 75.7 |
| 2-Winged | 1300 | 17700 | 16400 | 234 | 75.6 |
| 3-Winged | 13900 | 33400 | 19500 | 330 | 101 |

Across all scenarios, the selected vertiport sites tend to cluster around central Madrid, the main urban hub within the study area. This concentration can be partly attributed to the advantage that eVTOLs have in bypassing ground congestion, as car travel speeds are generally lower in the city centre. The analysis assumes that eVTOLs operate at their full cruise speed even over dense urban areas, although future airspace regulations may impose speed restrictions that could affect this assumption.

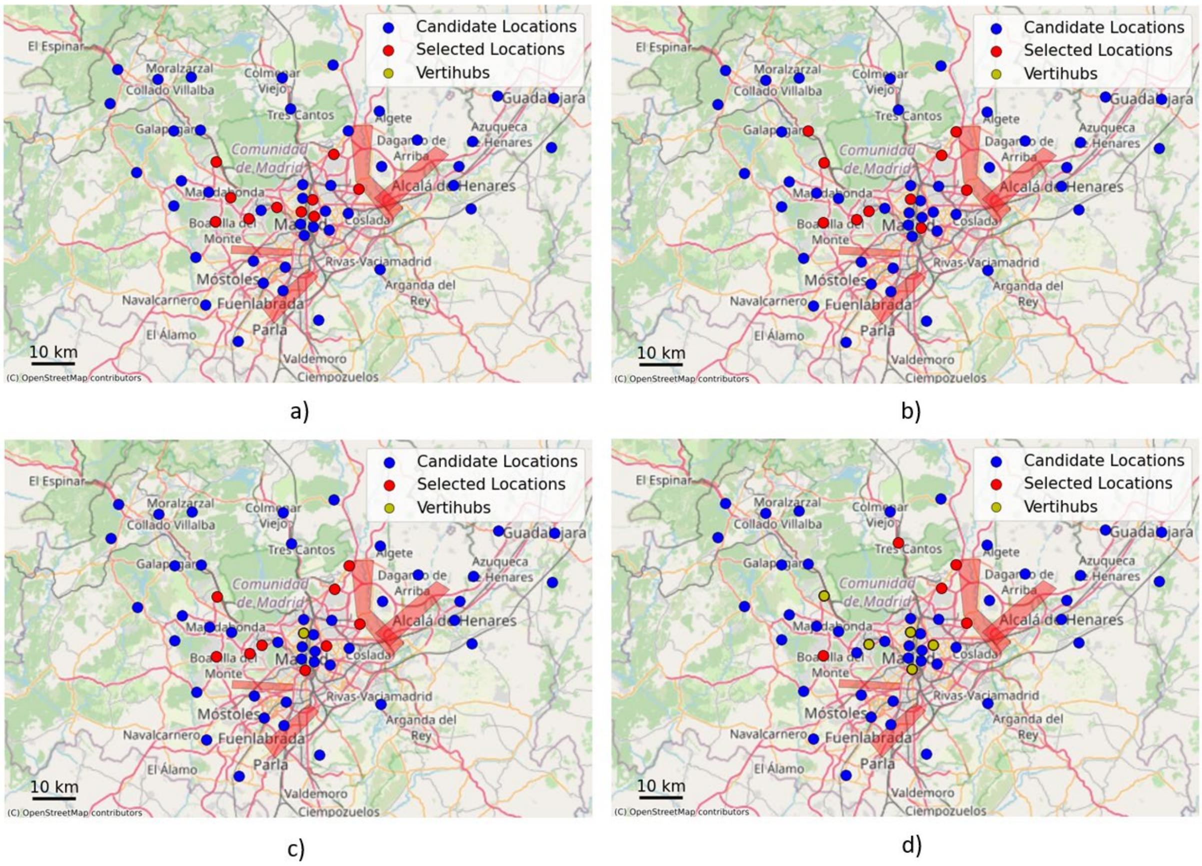


**Figure 11: Selected locations for: a) Scenario 1 with Multicopter; b) Scenario 1 with Winged eVTOL; c) Scenario 2 and d) Scenario 3**

The results also show that, under higher passenger demand, one of the central vertiports expands into a larger vertihub to accommodate additional traffic — a trend that continues in Scenario 3. Despite this, the spatial distribution of vertiports remains largely consistent: seven of the locations remain unchanged from Scenario 1 involving the Winged eVTOL configuration. In contrast, the Multicopter scenario shows a stronger concentration toward the city centre, where additional vertiports are installed. This pattern is likely driven by the smaller footprint of Multicopter vertiports, which makes them more feasible and cost-effective to construct in densely built-up urban areas.

Figure 12 presents the yearly profit as a function of $k_{max}$ and $c_{prices}$ for 150 simulated scenarios. The plots show that the zero-profit line (in black) exhibits an asymptotic behaviour, indicating that a minimum price threshold is required for the service to become profitable, mainly due to the limited capacity of the vertiports. Increasing the number of vertiports from 5 to 10 also expands the range of profitable scenarios, while the TTRP parameter has a noticeable impact on overall profitability. The Multicopter configuration proves profitable under a broader range of conditions. However, Figure 13 shows that the Winged eVTOL captures a substantially larger share of total demand, particularly once the Multicopter network becomes saturated. This is explained by the Winged eVTOL's higher passenger capacity (three versus one for the Multicopter) and greater cruise speed.



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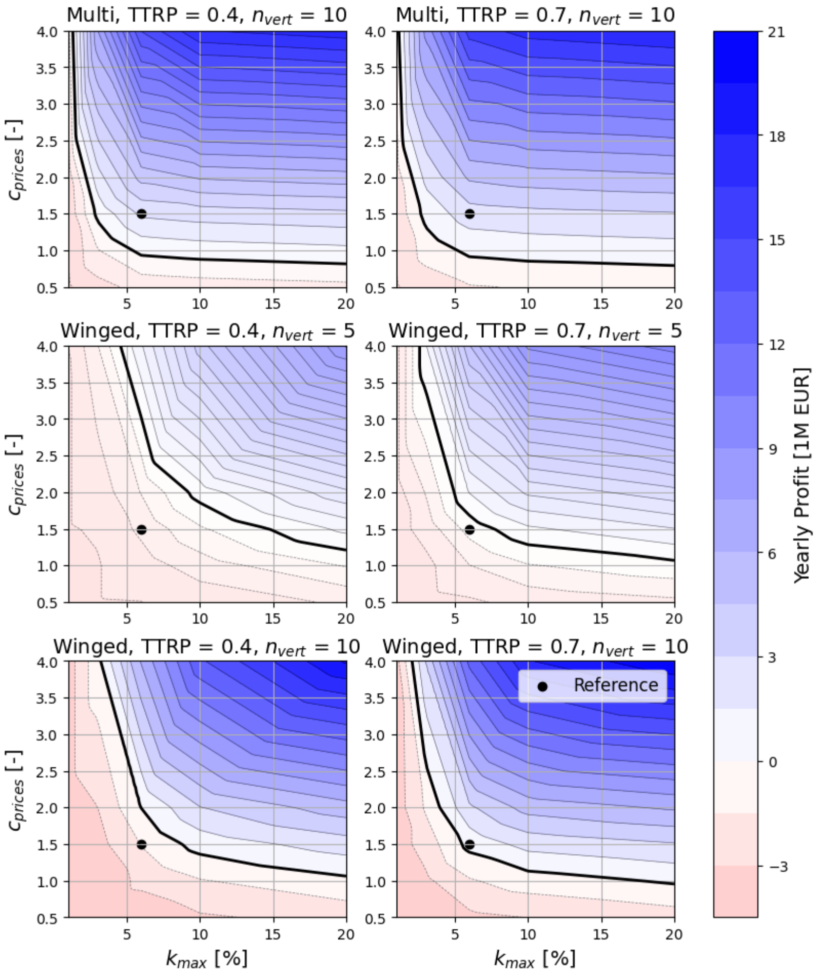


**Figure 12: Sensitivity analysis of the yearly profit. The reference point marks the values of cprices and kmax of the Scenario 2.**

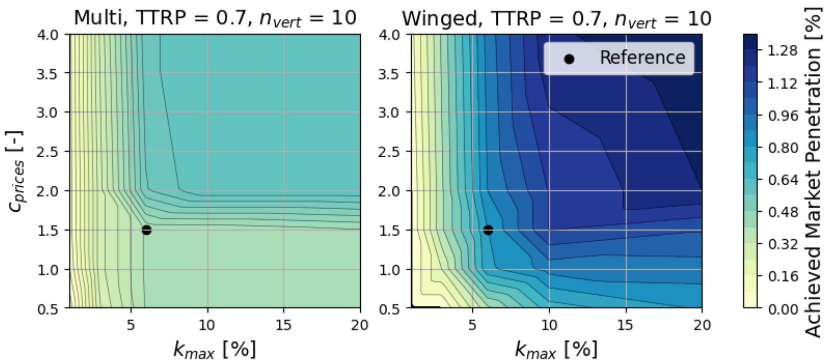


**Figure 13: Sensitivity analysis of the number of passengers. The reference point marks the values of cprices and kmax of Scenario 2.**

Figure 14 displays the mean distance, $d_{mean}$, for the scenarios with 10 vertiports. $d_{mean}$ reaches relatively high values when $k_{max}$ is low since overall demand in those cases is insufficient for any vertiport to operate profitably. As a result, the model tends to select sites with minimal or no demand but with lower floor costs, thereby minimising financial losses. Additionally, at $k_{max}$ = 20 [%], the chosen locations also deviate notably from those in the reference scenario. This happens because the higher demand causes many vertihubs to reach capacity limits, pushing the model to favor sites with lower floor costs even if their demand is smaller, as these locations can still operate near full capacity. Consequently, the selected locations are more influenced by assumptions about potential demand (through $k_{max}$) than by pricing parameters.

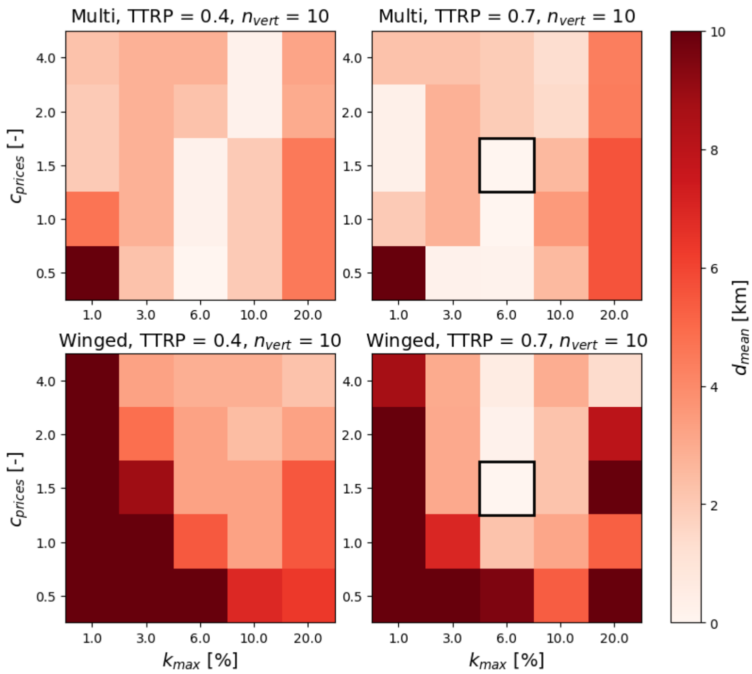


**Figure 14: Heat map showing the dmean values for the 100 scenarios with nvert = 10. The reference scenarios are outlined in black.**



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# 3 Conclusions, next steps and lessons learned

## 3.1 Conclusions

In this project, a tool was developed for optimising vertiport locations for passenger air mobility. The work began with a comprehensive review of vertiport location requirements, which was validated through consultations with stakeholders from industry and regulatory bodies. This process enabled the identification and prioritisation of the requirements to be incorporated into the Decision Support Tool (DST).

For the last-mile delivery use case, the optimisation problem was framed as a Maximal Covering Location Problem (MCLP), using employed population data with higher spatial resolution to estimate potential demand. A separate model was developed for the IAM passenger transport use case, in which the optimisation problem was formulated as a Hub Location Problem (HLP) with the objective of maximising the vertiport operator's profit. Air taxi demand was estimated from conventional taxi demand using MND-based OD matrices.

The tool was applied to two case studies in the province of Madrid, Spain. For the **last-mile delivery** use case, the model was found to be highly sensitive to the assumed influence radius of the lockers, but comparatively robust to other user-defined parameters. For the **passenger transport** use case, under a conservative scenario assuming limited adoption of the technology (up to 3% market penetration of road taxi demand), results indicated that operations with a large eVTOL featuring horizontal cruise capability would be unprofitable, whereas a smaller multicopter eVTOL could operate profitably. Sensitivity analyses further revealed that vertiport locations remained relatively stable under moderate adoption levels but varied significantly in scenarios of very low or very high adoption.

Throughout the duration of the project, the tool was significantly advanced toward industrial research maturity. Initially conceived as a conceptual framework based on existing literature, it evolved into a functional system comprising two independent mathematical models and implementations for the IAM use cases considered. By integrating input from industry and regulatory stakeholders into the design process, modules were identified and implemented that incorporate the most relevant and impactful requirements into the optimisation framework, thereby enhancing the tool's operational realism and applicability for future real-world deployment.

## 3.2 Next steps

The following next steps have been identified, which would require minimal restructuring of the current software implementation of the tool.

**For the last-mile delivery use case:**

- The model was found to be highly sensitive to the assumed influence radius. It is also plausible that the effective influence radius of a locker depends on the local population density. Therefore, improvements are recommended to make this parameter a function of contextual variables rather than a fixed user input. This enhancement could be achieved through a discrete choice model, although a dedicated survey would be required to collect the necessary behavioural data.

**For the IAM passenger transport use case:**

- The inclusion of price elasticity of demand is recommended, using a discrete choice model calibrated with survey data. The work being conducted in PRIAM [37] could serve as a methodological reference.
- Consider the effects (costs and benefits) on passengers and eVTOL operators as well to account for all stakeholders involved in the IAM system.
- Objective functions may include other non-economic effects (e.g., noise, visual pollution).
- Additional transport alternatives, such as ferries for inter-island connections, should be incorporated into the model to enhance its applicability to a wider range of geographical contexts.
- The car travel time model could be updated to account for deviations from straight-line routes caused by geographical barriers such as national parks, bodies of water, or mountainous terrain. This improvement would ensure that the model remains accurate beyond urban areas like Madrid.
- A shift to a graph structure for travel time estimation should be considered. This graph would include all different modes to compete with IAM (car, bus, train, ferry, airplane). Travel times and waiting times shall be included to the edges connecting nodes of the graph. GTFS files provide precise trip durations for scheduled modes (train, airplane and ferry). Tools such as Google Maps API or Open Street Maps can be used to give precise estimations of travel times between OD points.
- The use of OD matrices with higher spatial resolution should be tested to improve the precision of demand estimation.

In the longer term, the tool could be expanded by incorporating a microlocation model to identify specific feasible sites for vertiport construction based on EASA safety regulations and physical obstacles such as buildings or terrain elevation. Coupling this microlocation model with the current framework in a closed-loop configuration would enable both strategic and tactical siting decisions to be addressed within a single integrated solution, thereby facilitating decision-making for end-users.

## 3.3 Lessons learned

Overall, the project was considered successful in achieving its objectives, and the catalyst funding approach fitted the scope of the project. The lessons learned are listed below:

- The catalyst funding scheme for a one-year project proved to be effective. The scope of the project was identified already during the proposal and the objectives were very clearly defined. This was key to making the project possible in a one-year time frame.

- One limitation of the short duration was the restricted opportunity to include stakeholder feedback. A longer timeframe would have allowed the integration of insights gathered during the second workshop.
- The combination of a junior and a senior researcher was found to be highly productive and will be considered a best practice for future projects.
- It was observed that having an informal communication environment, such as a shared Microsoft Teams space, would facilitate quicker exchanges between mentors and consortium members.
- Compared to other projects where we have done online workshops, the workshops held in person in this project were very useful and created a lot of open discussions with contributions from most of the attendees.
- The light bureaucratic charge and small consortium size helped to focus on technical aspects and fulfilling the objectives of the project, which is key at this early stage of research.



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# 4 Dissemination

The table below summarises the dissemination actions carried out during the project.

**Table 5: Dissemination actions for the Engage 2 KTN Vertiports project**

| Action | Status | Event | Date | Further info |
|---|---|---|---|---|
| 1st Workshop presentation | Presented | Engage Vertiport 1st Stakeholders' Workshop | 23/01/2025 | 7 participants from Madrid city council, Madrid region, INECO, AERTEC and ENAIRE. |
| Airspace World 2025 presentation | Presented | Airspace World 2025 (conference) - Engage 2 workshop | 15/06/2025 | Alejandro Montoya (Nommon) presented an overview of the project. |
| 2nd Workshop presentation | Presented | Engage Vertiport 2nd Stakeholders' Workshop | 23/09/2025 | 6 participants from Madrid city council, Madrid region, INECO, IDOM and ENAIRE. |
| SIDs 2025 paper | Submitted | SIDs 2025 (conference) | 01/12/2025 | Paper on the main results of the project has been submitted to the conference. |

Apart from the mentioned actions, the project has created a set of technical deliverables that can be used to disseminate the findings of the project:

- D2.1 Analysis of requirements for vertiport location [1]
- D3.1 Optimal vertiport location model [2]
- D4.1 Optimal vertiport location DST [3]
- D5.1 Case study report [4]

In addition, deliverable D6.1 Dissemination and exploitation report [5] has been created. It details the communication goals, high-level messages and a short description to be broadcasted in different media with the aim of making the project understandable at a first glance. The deliverable also details the strategy the project followed to make use of or disseminate the project’s results. The exploitation charter explains the project’s approach and strategy to make the best use of the project results.

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# 6 List of acronyms

| Acronym | Description |
|---|---|
| AEMET | Agencia Estatal de Meteorologia |
| ASOS | Automated Surface Observing System |
| ATM | Air Traffic Management |
| DST | Decision Support Tool |
| eVTOL | Electric Vertical Take Off and Landing |
| FATO | Final Approach and Take Off |
| GIS | Geographical Information Systems |
| HLP | Hub Location Problem |
| IAM | Innovative Air Mobility |
| MCLP | Maximal Covering Location Problem |
| MILP | Mixed Integer Linear Programming |
| MND | Mobile Network Data |
| NPS | Net Promoter Score |
| OD | Origin Destination |
| TTRP | Travel Time Ratio Parameter |
| UAM | Urban Air Mobility |