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DOI
10.1016/j.jairtraman.2025.102757

Publication date
2025

Document Version
Final published version

Published in
Journal of Air Transport Management

Journal of Air Transport Management 125 (2025) 102757

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Multi-objective vertiport location optimization for a middle-mile package delivery framework: Case study in the South Holland Region

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ARTICLE INFO

Keywords:
Urban air mobility
Vertiport location
Demand optimization
Tabu search

ABSTRACT

With the rapidly increasing pace of urbanization and high demand for efficient modes of transport, the Urban Air Mobility (UAM) market has seen a remarkable growth in the past years. This is especially the case for the transportation of goods. Using UAM for cargo operations is likely through operating on Middle-Mile Delivery (MMD) missions to transport cargo between facilities or distribution centers in an operator's network. The efficiency and practicality of such a network are largely affected by the selection of strategic positions for vertiports. As vertiport location optimization is underexplored in current scientific research this paper aims to fill this research gap by developing and analyzing a multi-objective optimization model for the placement of vertiports for a middle-mile package delivery system, considering capacity, available land space, safety and noise impact factors. We develop a novel Multi-Objective Multiple Allocation Capacitated p-Hub Coverage Problem framework for an MMD UAM network and test it using the South Holland region as a case study. Notably, the model can easily be converted to other cities. First, to reduce computational efforts, the K-means clustering algorithm is proposed. This is used to divide 6625 zones into a number of K clusters, with each cluster representing a vertiport candidate location. Furthermore, we present a multi-objective Tabu Search based heuristic optimization algorithm to solve the optimization problem. The impact of different factors such as number of clusters, number of vertiports, drone range, maximum safety distance, and turn around time The presented model provides decision-makers with the ability to assess the suitability of a region for the implementation of a UAM MMD system and aids in the identification of potential good locations to set up vertiports. We demonstrate that an increase in the number of vertiports leads to a higher attainable demand coverage, however, this results in a steep drop-off in terms of safety and noise nuisance performance. Furthermore, the results show that an increase in drone range, maximum safety distance or a decrease in turn around time allow for overall better performing vertiport networks.

1. Introduction

The ever-increasing pace of urbanization and the high demand for efficient transportation options have spurred cities into a phase where traditional transportation methods are being redefined. One promising innovation that offers a high potential value is Urban Air Mobility (UAM), which offers transportation options for both passengers and cargo. The momentum in this field is demonstrated by initiatives such as Uber Elevate (Holden and Goel, 2016) and Amazon Prime Air (Amazon, 2022). Additionally, companies such as Zipline have already utilized small Unmanned Aerial Vehicles (sUAVs) for the transportation of goods (Zipline, 2023).

Existing research focuses on the transportation of people in the form of on-demand transportation or so-called air taxis (Brunelli et al., 2023; Macias et al., 2023). In contrast, much less research has been done on the delivery of goods (Gunady et al., 2022). Furthermore, papers that consider this business model mainly focus on a last-mile delivery using sUAVs, which refers to the segment of the delivery from the final distribution center or warehouse to the destination of the package. In contrast, very little research exists on the concept of Middle-Mile Delivery (MMD). MMD refers to the delivery segment of the logistics chain between two nodes in an operator's network. For example, the segment of transport from a large warehouse to a more centrally located distribution center. MMD is an interesting use case for UAM as it has the potential to improve rapid delivery, relieve road congestion, and improve accessibility. Furthermore, using drones for MMD could also result in a reduction in operating costs as they do not require manned operations.

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https://doi.org/10.1016/j.jairtraman.2025.102757
Received 4 September 2024; Received in revised form 1 January 2025; Accepted 10 February 2025
Available online 26 February 2025

Regardless of the application, the setup of a UAM network imposes a decision-making problem on the positioning of airports for aircraft that take off and land vertically, commonly referred to as vertiports (VPs). The positioning of vertiports can have a large influence on the practicality and efficiency of the system. Moreover, placing vertiports in an urban area is largely affected and constrained by public opinion. According to a study performed by the European Union Aviation Safety Agency (EASA), the main public concerns are safety, (cyber)security, environmental impact, and noise pollution (European Union Aviation Safety Agency (EASA), 2021). Of these concerns, safety and noise can be taken up in the decision-making process of where to place vertiports as they are highly related to the area surrounding the vertiport. For safety, this entails looking into safety distances and potential hazards that a location poses for drone operations. For noise, it is preferred to place vertiports at locations that already generate high amounts of noise to reduce nuisance. This idea was first proposed by Antcliff et al. (2016) suggesting that highways and main roads of the city could function as noise absorption zones caused by the propulsion of the vehicles.

To aid in the decision-making process of placing vertiports for a UAM MMD delivery concept, this work proposes an optimization model that integrates three key metrics: demand satisfaction, safety, and noise. The model serves as an innovative framework to perform an initial analysis on the suitability of setting up an MMD UAM network in any urban environment. As the solution space for the posed problem will be very large, it is proposed to use a meta-heuristic algorithm to efficiently search said solution space. The framework that is proposed for this research builds on the framework of Gunady et al. (2022) and the work of German et al. (2018) and aims to fill gaps in the existing literature by providing a multi-objective optimization model, considering multiple origin locations (e.g. warehouses) and safety metrics. Furthermore, while the Tabu Search (TS) algorithm has been shown to perform very well for facility location problems compared to other meta-heuristics such as the Genetic Algorithm (GA) and Simulated Annealing (SA) (Arostegui, 1997), TS has not been used in a UAM context. Therefore, this work introduces a Tabu Search-based heuristic algorithm that can be used for solving multi-objective vertiport location optimization problems. This translates to the following research objective: ***To develop and analyze an optimization model for the placement of vertiports for a middle-mile package delivery system, considering capacity, safety, and noise impact factors.*** The proposed framework is applied to the South Holland region to test it in a use case.

The remainder of this paper is structured as follows. First, Section 2 provides an overview of the current state-of-the-art in vertiport location optimization. Section 3 explains how a user may use the framework for an assessment of the potential UAM vetiport network in a given city. This is then followed by Section 4 which describes the methodology. In Section 5, a case study for the South Holland district is presented. This is followed by Section 6, which describes the experimental setup. The results are then presented and discussed in Section 7 and Section 8, respectively. Finally, the conclusions and recommendations are given in Section 9.

2. Literature review

This section aims to present the current state-of-the-art considering vertiport positioning techniques and optimization methods. Vertiport positioning currently is performed in three ways in existing literature: through the use of Geographical Information Systems (GIS), the K-means clustering algorithm, or by performing vertiport location optimization in an objective-based optimization.

GIS are systems that can be used to capture, analyze and visualize data in a spatial context. In vertiport positioning context, GIS are used to find and select suitable locations for the construction of vertiports. In literature, it has been used to assess factors such as socio-economic variables, points of interest and existing heliports. Fadhil (2018) depicted regional suitable areas for vertiports in Munich and Los Angeles subject to constraints on restricted flight zones, military areas and schools. Similarly, Gonzales (2020) uses socio-economic factors in combination with a rooftop footprint and flatness analysis to determine suitable vertiport locations. Kim and Yoon (2021) perform a feasibility analysis for UAM applications based on population density and airspace restrictions in San Francisco and New York. Finally, Brunelli et al. (2022) created a digital twin of the city of Bologna and use building height, type and obstacle clearances to assess location suitability. While literature using the GIS approach provides great insights into location or region suitability of vertiports, no information can be provided on the UAM network performance as a whole or the application objective efficiency (e.g. demand coverage, cost minimization, travel time minimization).

The second method used in literature for vertiport positioning is the K-means clustering algorithm as described by Schütze et al. (2008). The algorithm aims to group data points into a number of K clusters by minimizing the average squared Euclidean distance between cluster centers and the respective data points. In UAM context, this means that the distance between potential vertiport locations and the origin or destination is minimized for a network with an amount of K vertiports. Due to the nature of this algorithm, it is often used for the optimization of on-demand air mobility networks. Lim and Hwang (2019) use the K-means algorithm to choose the appropriate number of vertiports and their locations based on travel time savings for an on-demand mobility network in the city of Seoul. This is done with the assumption that the closest centroid to the starting and destination points are the arrival and departure points. The downside of using the K-means clustering algorithm is that it starts out with a random initial solution, which has a large influence on the quality of the outcome (Usman et al., 2013). Therefore, Rajendran and Zack (2019) proposed a multimodal transportation based warm start technique, in which they feed an initial solution to the K-means algorithm based on the determined fitness of locations. Similarly, Sinha and Rajendran (2022) proposed a multi-criteria warm start technique based on socio-economic factors. Although the K-means algorithm is at the base of some works that provide meaningful insights in vertiport location optimization for air taxi services, it lacks the ability to effectively optimize for objectives other than distance. Consequently, in literature, it is mostly used to identify potentially suitable and favorable vertiport locations for an air taxi network.

Finally, the third vertiport positioning method used in literature is objective based optimization. Generally, Vertiport Location Optimization (VLO) is posed as a type of Hub Location Problem (HLP), which consist of locating hub facilities and designing hub networks so as to optimize a cost- or service-based objective. The first mathematical formulation of an HLP was posed by Campbell (1994) which has been adapted for VLO a number of times (Shin et al., 2022; Rath and Chow, 2022). Generally there are three types of HLPs. These are the p-hub median problem, the p-hub center problem and the p-hub coverage problem, with the difference being the optimization objective. The median problem aims to minimize the total transportation cost (e.g. monetary, time, energy). The center problem is defined by a MiniMax criterion which contains the objective to minimize the maximum cost of origin destination pairs in terms of money, time or distance. Finally, the coverage problem tries to maximize the coverage of a network. Due to the fact that the MMD UAM network effectiveness should be assessed, the p-hub coverage problem is the most appropriate type of HLP for the problem at hand. Furthermore, HLPs are also defined by characteristics such as the inclusion of capacity constraints on hubs or flows and whether each destination is allocated to one hub (single allocation) or multiple hubs (multiple allocation).

Similar to the K-means approach, objective based optimization has mainly been used for assessing the benefits of air taxi networks (Macias et al., 2023; Wei et al., 2020; Shin et al., 2022; Rath and Chow, 2022). Holden and Goel (2016) proposed a clustering algorithm to cluster demand points into candidate vertiport locations, after which

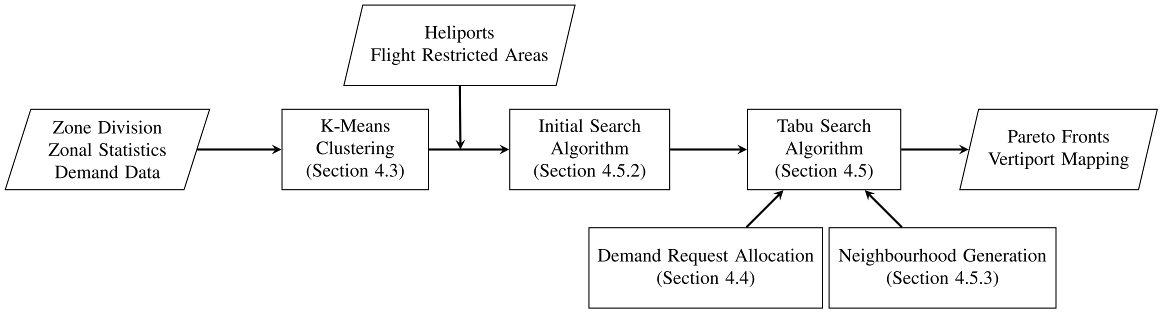


Fig. 1. Overview of the vertiport location optimization framework.

facility location algorithm is used to maximize trip coverage. Rath and Chow (2022) optimized a vertiport network for demand coverage of air-taxi's formulating it as a ridership maximization problem. While these works pose interesting insights in the general field of vertiport location optimization, they are all focused on the transport of people while considering a single objective. To scale HLPs to larger sizes and use it for an MMD concept, the aforementioned methods should be utilized and integrated into a single model considering multiple objectives.

Therefore, this work proposes to use a combination of all three methods to develop a model that is capable of optimizing and analyzing a UAM network, considering placement of vertiports for middle-mile package delivery whilst considering vertiport capacity, available land space, and safety and noise impact factors. Where GIS will be used to analyze zonal characteristics, the K-means algorithm will be used to slim down the solution space and finally, the problem will be solved using a multi-objective Tabu Search based heuristic algorithm to be able to capture Pareto fronts. This framework adds to the existing state-of-the-art in a several ways. It combines a number of existing methods which are then applied to a new concept, being vertiport location optimization for MMD using UAM, which has been insufficiently studied in the literature. It therefore seeks to innovate in its application. To be more specific, the framework adds to the existing state-of-the-art as the first multi-objective vertiport optimization model for MMD. Additionally, it is also the first framework to consider multiple origin points, vertiport capacity, safety risks, and noise nuisance for optimizing vertiport locations in a UAM network for MMD.

3. Framework usage

Fig. 1 shows an overview of the different steps within the framework to determine optimal vertiport locations. The inputs for the model are the zone division, zonal statistics, and demand data defining the location where the UAM vertiport network is to be inserted. Next, a K-Means Clustering is used to reduce the number of zones to a computationally viable amount, if necessary. The Tabu Search Algorithm is employed to find the optimal location for vertiports. A multi objective optimization between demand served, safety risks, and noise nuisance is performed. Consequently, the framework outputs a Pareto front showing the resulting of balancing all objectives. The user can select the vertiport network locations for a specific solution of the Pareto front.

As an example, for the region of South Holland, the model may output a Pareto front as shown in Fig. 2(a). This contour can be used to provide insights into the trade-off between the three objectives: demand coverage, safety risks, and noise nuisance. All possible solutions found during the optimization are mapped in the Pareto front. In case there is a heavy preference for one of the three objectives, decision-makers may choose one of the solutions that perform best in a single objective. These are indicated in the figure by the star markers. The model then provides the areas that correspond to the selected solutions and maps them. The solutions corresponding to the best demand coverage and least safety risks are shown in Fig. 3.

In reality, the selection of a suitable solution will most probably not be based on a complete priority of a single objective. Rather, it will be based on a trade-off between the three objectives subject to minimum requirements. For example, whether or not a UAM MMD network is implemented, is likely dependent on the demand coverage that can be realized. For the purpose of demonstration, we assume that a minimum coverage of 45% is deemed acceptable to implement a network. In this case, the solutions located in the bottom left of the Pareto front become non-viable solutions. With the leftover viable solutions, a new sub Pareto front can be constructed considering the safety and noise objectives. This is illustrated by Fig. 2(b). This Pareto front contains the most interesting solutions as they adhere to demand coverage constraint while performing the best in terms of safety risks and noise nuisance.

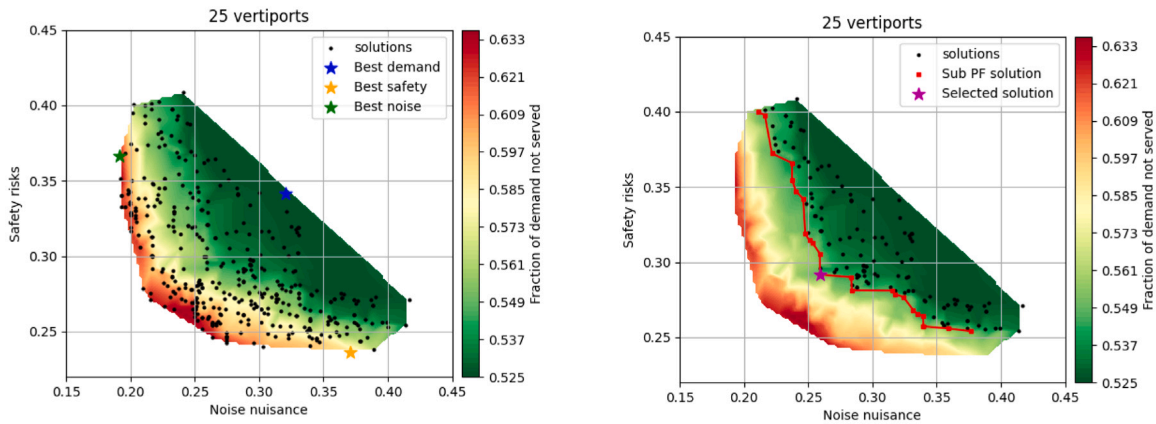
The framework allows companies to identify potential vertiport networks and aids in decision-making on investments. Analysis of the Pareto front, that is created for a specifically chosen set of input parameters, can be used to assess whether or not a certain urban area is suitable for the implementation of an MMD network using UAM. The question is whether solutions exist that perform well in terms of demand coverage, safety risks, and noise nuisance. An area can be seen as particularly suitable if it adheres to some minimum demand coverage while offering networks that contain low safety risks and little noise nuisance. This gives decision-makers an immediate impression of the effectiveness of implementing a vertiport network for MMD with the desired inputs. Furthermore, the framework can then be used for decisions on whether to invest on a higher amount of vertiports, increasing ground efficiency processes, or selecting a better performing drones. Finally, the Pareto front enables companies to assess and prioritize their preferences in balancing the three objectives.

4. Methodology

In this section, first, a brief description of the concept of operations is given in Section 4.1. Second, the mathematical model that is implemented is described in Section 4.2. Next, Section 4.3 explains the K-means clustering algorithm and the warm start technique. This is then followed by a description of the demand request allocation algorithm in Section 4.4. Finally, the section is concluded by a description of the Tabu Search heuristic algorithm used to find the Pareto fronts in Section 4.5.

4.1. Concept of operations and assumptions

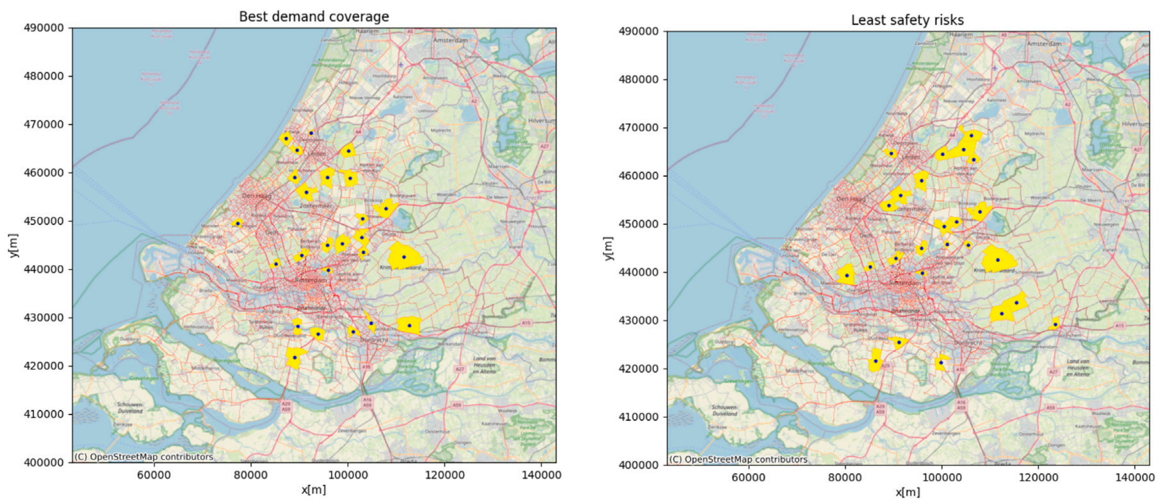
As mentioned, the selected application is a middle-mile delivery system for parcels in an urban environment. In the proposed framework, drones fly with a number of packages from the origin warehouse to a vertiport close to the destination zone of the packages. At the vertiport, the drone lands, is unloaded, and either the battery is swapped or the drone is charged. After, the drone immediately flies back to its origin warehouse. The vertiport then serves as a distribution center where packages are temporarily stored. Furthermore, the following assumptions are made in order to simplify the complexity of the model:



(a) Pareto front for business case example scenario

(b) Pareto from considering a minimum of 45% demand coverage

Fig. 2. Example of pareto front output.



(a) Vertiport locations for best demand coverage

(b) Vertiport locations for least safety risks

Fig. 3. Example of vertiport mapping output.

- The last-mile delivery of the packages that are temporarily stored at a vertiport is done by courier or self-pickup.
- Warehouses are suitable locations for vertiports. Drones can directly depart from the warehouse locations.
- Warehouses are assumed to be able to store the entire fleet of drones operating.
- No limit is set on the fleet size of drones.
- At most one vertiport can be placed in each of the zones.
- A vertiport is able to cover an entire zone.
- The geographical centroid of each zone represents the candidate vertiport location accurately enough to be used for distance calculations.

4.2. Mathematical model

To translate the proposed framework into an optimization problem, a mathematical model is developed. Consistent with existing literature, the problem is defined as a type of Hub Location Problem. The mathematical model provided is based on the works of Maleki et al. (2023) and Nickel et al. (2016). The developed mathematical model contains multiple objectives and introduces capacity constraints on the vertiports. This capacity represents the number of pads in the vertiport, which determines the volume of drone traffic (landings and take-offs) that the vertiport can handle. Furthermore, as the first objective is to minimize the demand that cannot be served (maximizing the coverage), it is categorized as a p-Hub coverage problem. Finally, due to the fact that multiple vertiports can be used to serve a single destination, it is modeled as an HLP with multiple allocation. Therefore, the complete mathematical model can be categorized as a Multi-Objective Multiple Allocation Capacitated p-Hub Coverage Problem.

4.2.1. Sets and parameters

The mathematical model contains the number of sets, decision variables and parameters. These are presented below.

Sets:

N:	The set of all nodes containing zones and warehouses
K:	The set of selected vertiport locations
T:	The set of vertiport types (i.e., small: 1 pads, medium: 4 pads, and large: 16 pads)
D:	The set of origin–destination combinations

Decision variables:

z_k^t:	Binary variable: 1 if a hub of type t is located in zone k

R_{ij}^k: Continuous variable between 0 and 1 representing the fraction of demand shipped from node i to node j routed through a vertiport in zone k

Parameters:

W_{ij}: Demand from origin node i to destination node j

SH_k: Safety score of vertiport location zone k related to the maximum height of buildings - a higher value indicates taller buildings

SM_k: Safety score of vertiport location zone k related to the mean height of buildings - a higher value indicates taller buildings

SP_k: Safety score of vertiport location zone k related to the population density - a higher value indicates a more densely populated area

N_k: Noise score of vertiport location zone k related to the maximum speed of cars - a higher value indicates a higher maximum speed

p: The number of vertiports to be located

v_{ij}^k: A binary variable assuming the value of 1 if a vertiport in zone k is able the cover the journey from origin i to destination j

Γ_t: The capacity of a vertiport of type t

s^t: Infrastructural space required for a vertiport of type t

I_k: Infrastructural space available in zone k

d: Distance to the closest vertiport or heliport

d_{min}: Minimum distance to a heliport and between vertiports

d_{max}: Maximum distance to a heliport or between vertiports for safe emergency landings

$A^{operational}$: Aerial space needed for operating a vertiport

$A_k^{unrestricted}$: Aerial space available in zone k that is not affected by flight restrictions

4.2.2. Objectives

The framework is set to have three objectives, the first of which is defined by the fact that a hub covering problem is chosen. As shown in Eq. (1), it aims to minimize the fraction of demand not served. This objective is chosen in order to be able to assess and reflect on the effectiveness of implementing an MMD concept in an urban environment.

$$\textbf{minimize} \quad 1 - \sum_i \sum_j \sum_k W_{ij} R_{ij}^k \tag{1}$$

The second objective, in Eq. (2), minimizes the safety scores of the chosen vertiport locations. This can be seen as the associated risk of implementing a network of vertiports. Three main safety impact variables are selected. The first and second safety variable are related to proximity to highrises. Placing vertiports near tall buildings raises safety concerns in terms of obstacle hazards, resulting in an enhanced collision risk during critical take-off and landing flight phases. Furthermore, tall buildings are known to disrupt airflow patterns which can create unpredictable wind and turbulence conditions with high wind speeds, which in turn poses safety risks to aircraft. For each zone in the network, the maximum and the mean building height are taken and the values are normalized using the min–max normalization method. This results in a maximum height safety score SH_k and a mean height safety score SM_k for each zone. The third safety variable considered relates to population density. Zones with a higher population density are less preferable due to an increased risk of casualties in emergency situations. Similar to the first two variables, the population density of each of the zones in the study area is taken and the min–max normalization method is used to normalize the values.

$$\textbf{minimize} \quad \sum_k \sum_t (SH_k + SM_k + SP_k) z_k^t \tag{2}$$

Finally, the third objective, as given by Eq. (3), tries to minimize the nuisance caused by the additional noise that would be generated if a set of k vertiports were to be accepted as a network. For this, the highest maximum speed in a zone is used. This stems from the suggestion that highways and main roads of a city already generate high amounts of noise. Therefore, the additional noise caused by the presence of a vertiport will cause less nuisance (Antcliff et al., 2016). The highest maximum speed is chosen as opposed to the mean due to the fact that most zones also contain a lot of small roads with a very low maximum speed. Considering the mean might overlook zones with a highway generating significant noise, as this could be offset by the presence of many small roads. Meanwhile, the zone could be a very good vertiport location in terms of noise due to the presence of this large highway. The noise impact variable is also normalized using the min–max normalization method.

$$\textbf{minimize} \quad \sum_k \sum_t N_k z_k^t \tag{3}$$

4.2.3. Constraints

The main constraints are given in Eqs. (4)–(11). The first constraint, shown in Eq. (4), ensures that the model selects precisely p amount of vertiports. The second constraint, given by Eq. (5), relates to coverage capability. It ensures that a demand flow from node i to node j, can only be routed through a vertiport in zone k if the drone has enough range to fly from node i to the vertiport in zone k and the last-mile distance from the vertiport in zone k to destination j is not too large. The limit on the last-mile distance is also constrained to prevent packages from ending up too far from the their destination, to the point where there is no use in transporting it using a drone. Next, the third constraint, Eq. (6) ensures that no more flow is routed through the vertiport in zone k than the capacity that it has. The fourth constraint, given by Eq. (7), states that a vertiport of type t can only be positioned in a zone if there is enough infrastructural space. Furthermore, the fifth constraint, in Eq. (8), sets safety distance limits and ensures that a vertiport has a minimum distance to the nearest vertiport and heliport to avoid collision risks. Moreover, it also ensures a maximum distance to the nearest vertiport or heliport, to account for emergency landings if necessary. The sixth constraint, in Eq. (9), ensures that vertiports can only be positioned in zones where the area that is not restricted by no-fly zones is large enough to accommodate for the necessary flight operations. The constraint given by Eq. (10) makes sure that the fraction of demand shipped from node i to j through a vertiport in zone k can take any value between 0 and 1. Finally, Eq. (11) defines the variables v_{ij}^k and z_k^t to be of binary type. Where v_{ij}^k represents whether a demand request from origin i to destination j can be routed through a vertiport in zone k and z_k^t represents whether a vertiport of type t is placed in zone k.

$$\sum_t \sum_k z_k^t = p \tag{4}$$

$$R_{ij}^k \le \sum_t \sum_k v_{ij}^k z_k^t \quad , \forall i, j \in N \ \& \ \forall k \in K \tag{5}$$

$$\sum_i \sum_j W_{ij} R_{ij}^k \le \sum_t \Gamma_t z_k^t \quad , \forall k \in K \tag{6}$$

$$\sum_t z_k^t S^t \le I_k \quad , \forall k \in K \tag{7}$$

$$d_{min} \le \sum_t z_k^t d \le d_{max} \quad , \forall k \in K \tag{8}$$

$$\sum_t z_k^t A_{operational} \le A_{unrestricted}^k \quad , \forall k \in K \tag{9}$$

$$0 \le R_{ij}^k \le 1 \tag{10}$$

$$v_{ij}^k, z_k^t \in \{0, 1\} \tag{11}$$

4.3. K-means clustering algorithm

As HLP problems are generally NP-hard in nature, a clustering algorithm is used to reduce the solution space size. For this, the K-means algorithm is chosen due to its heavy presence in existing literature as discussed in Section 2. The K-means algorithm, as first described by Schütze et al. (2008), aims to cluster a set of data points into a prespecified K amount of clusters. The different clusters are identified by minimizing the average squared Euclidean distance, also known as the residual square sum of squares (RSS), between cluster centers and the respective data points. A cluster center is defined as the mean or centroid μ of cluster ω. The equations to calculate the centroids and the RSS are given by Eq. (12) and Eq. (13), respectively.

$$\vec{\mu}(\omega) = \frac{1}{|\omega|} \sum_{\vec{x} \in \omega} \vec{x} \tag{12}$$

$$RSS = \sum_{k=1}^{K} \sum_{\vec{x} \in \omega_k} |\vec{x} - \vec{\mu}(\omega_k)|^2 \tag{13}$$

The algorithm starts with a random selection of the initial centroids as a seed solution. The algorithm then moves the centroids around in space to minimize the RSS iteratively. In each iteration, the data points are first reassigned to the cluster with the closest centroid, after which the location of the centroids is recomputed. This is repeated until the centroids do not change between iterations, indicating that the algorithm has stabilized. To prevent the algorithm from running indefinitely, a second algorithm termination criterion of 1000 iterations is set.

4.3.1. Area constraint

As a single vertiport is assumed to cover an entire zone, there is a necessity to set an area constraint on the cluster size in the algorithm. This relates to the fact that with a larger cluster size, one loses a level of detail of the area. For example, for a cluster of six zones that all have a very large area, the assumption that a single vertiport is able to cover that entire cluster does not hold. It is therefore assumed that a cluster may have a maximum area of $100\ \mathrm{km}^2$ such that it maximally covers an area of 10x10 km. This ensures that the last-mile distance within a single zone does not become too large. In addition to this, whereas the centroid of a zone is used for the vertiport location in any distance calculations, this might not be the case in reality. The vertiport can be placed anywhere inside the zone. Therefore if the area of a zone becomes too large, there could be a misconception on the necessary range for drones to reach the vertiport.

4.3.2. Warm start solution

A drawback to the K-means algorithm is that it starts out with a random initial solution, which has a large influence on the quality of the outcome (Usman et al., 2013). It is therefore suggested to implement the warm start technique. This entices inputting an initial solution of good quality as a starting point. In the chosen capacity constrained MMD network context, each vertiport has a maximum capacity of packages that can be handled throughout the day. As a result, areas containing a high demand require a greater amount of vertiports to allocate this demand. Therefore, it is chosen to input the K locations with the highest demand as a warm start solution for the K-means algorithm. This results in a higher amount of clusters centered around areas with high demand, allowing for more vertiports in those areas.

4.3.3. Clustering score factors

In the clustering process, each of the identified zones and their respective characteristics are added to a cluster. To assign a new score or to compute the metrics for the new clusters, several decisions are made:

- Demand: Assign demand from zones to according cluster.
- Safety - Maximum Height: Find maximum height of all zones and assign to cluster.
- Safety - Mean Height: Average the mean height of all zones and assign to cluster.
- Safety - Population Density: Recalculate population density for new clusters.
- Noise - Maximum car speed: Find the average of the maximum car speed of zones and assign to cluster.
- Unrestricted flight area: Recalculate unrestricted flight area for new cluster.
- Infrastructure space: Find highest category of infrastructure space and assign to cluster.

In terms of demand, the origin–destination pairs are adjusted to fit the new clustered zones. Although the origin locations stay the same, destinations are now inside a cluster, resulting in a reduction of origin–destination pairs. For the safety score, three characteristics are clustered: the maximum building height, the mean height, and the population density. For the maximum height, the absolute maximum height of the new zone is used as this characteristic is meant to look at the peak value. For the mean height, the mean of all zones within the cluster is taken. Furthermore, the population density is recalculated for the new zones. In terms of noise, the maximum car speeds of the zones are averaged and set as the value for the new cluster. This is done to compensate for situations where a cluster contains zones with highways as well as zones with residential areas, which are on opposing ends of the spectrum in terms of noise nuisance. The flight restrictions, which are introduced in the model as unrestricted flight areas, are recalculated for the clusters. Finally, for the available infrastructure space, the highest category of the zones in a cluster is chosen.

4.3.4. Adapted algorithm

The resulting K-means algorithm with the aforementioned adaptations due to the considered application is shown in Algorithm 1.

Algorithm 1 Adapted K-means algorithm

Input: Set of all zones Z (zone_number, centroid $\vec{x_z}$, demand), Number of clusters (K)
Output: Cluster assignment label (ω_z) for each of the zones, Set of zones assigned to cluster k (ω_k),
    Set of cluster centroids ($\vec{\mu}$)
Function:
Initial centroids $\vec{\mu}$ = K nodes with largest demand
while Stopping criterion is not met **do**
  for z = 1 to Z **do**
    Assign closest cluster to zone $\omega_z = argmin|\vec{\mu} - \vec{x_z}|$
    for k = 1 to K **do**
      Calculate cluster areas A
    while any A_k **in** $A > 100km^2$
      Move centroids of clusters with too large area towards point in cluster closest to average area of cluster
      $\vec{\mu_k^{new}} = 0.5(\vec{\mu_k^{old}} + \vec{x_{avg}})$
      Assign closest cluster to zone $\omega_z = argmin|\vec{\mu} - \vec{x_z}|$
      Recompute cluster areas A
    for k = 1 to K **do**
      Recompute centroids $\vec{\mu}_k = \frac{1}{|\omega_k|} \sum_{\vec{x_z} \in \omega_k} \vec{x_z}$

4.4. Demand request allocation algorithm

There are two factors that influence the demand objective score as presented in Eq. (1) in Section 4.2.2. These are the (1) set of vertiports that is selected as a solution and (2) the allocation of demand requests. To compute the demand objective score of a given solution, the given demand requests, consisting of an origin–destination pair and the parcel demand, must be assigned to a vertiport. The allocation strategy chosen for the proposed framework is to select the closest vertiport to the

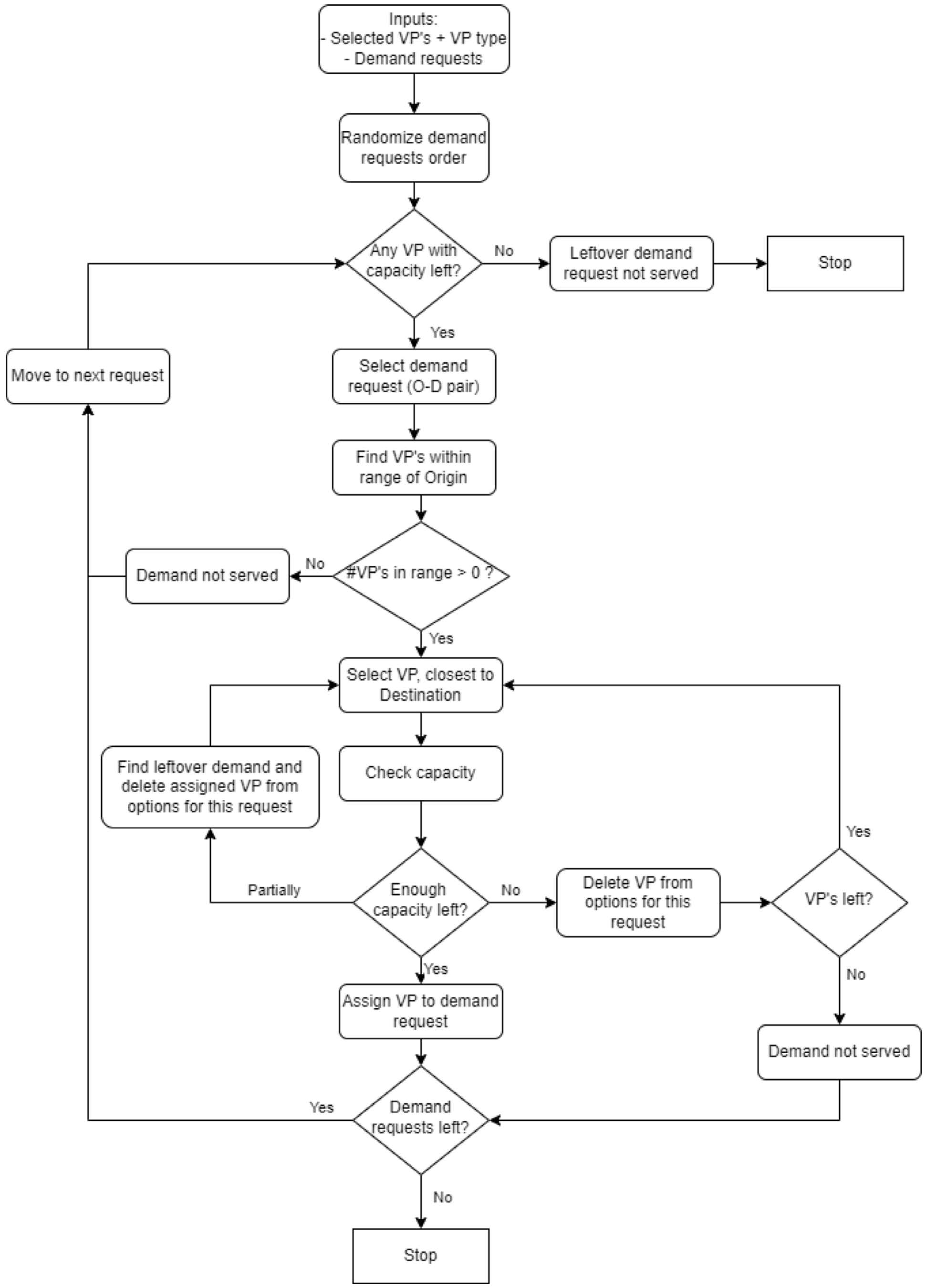


Fig. 4. Demand request allocation algorithm.

destination zone, that lies within the selected drone flight range of the origin warehouse, subjected to capacity constraints. This is done under the assumption that it is preferred to use the flight mode of transport as much as possible. This assumption is in line with the goal of the MMD concept to relieve road congestion and improve rapid delivery. The demand request allocation algorithm that is developed, following this assumption, is shown in Fig. 4. The algorithm takes the selected vertiports, their types (for capacity), and the demand requests as inputs and outputs the associated percentage of demand served.

4.5. Tabu search algorithm (TSA)

Due to the high complexity of the problem and its large solution space, it is not possible to try all possible solutions. Therefore, the solution space must be searched in an efficient manner to find a near-optimal Pareto front. Following the identified research gaps, a Multi-Objective TSA that can be used for the proposed framework is developed. This TSA is based on the work of Jaeggi et al. (2008). First, a description of the memories used by the algorithm is given in Section 4.5.1. Next, Section 4.5.2 presents an algorithm to find an initial feasible solution. Section 4.5.3 follows with the set-up of the neighborhood structure. Finally, Section 4.5.4 concludes with a description of the different moves that the algorithm can perform in the solution space and an overview of the entire algorithm.

4.5.1. Algorithm memories

To capture the Pareto front and efficiently explore the solution space, the algorithm works with three types of memories: the Short

Term Memory (STM), the Medium Term Memory (MTM), and the Intensification Memory (IM). The STM stores the points that are visited by the algorithm and may not be revisited, commonly referred to as the tabu list. The MTM stores the optimal solutions that are found and is used to restart the search, following a diversification that yields no good solutions. Finally, the IM is used to store optimal or near optimal solutions, that are not selected to be the new current solution at the end of an iteration step. Furthermore, a local iteration counter i_{local} is used to define the algorithm's ability to intensify, diversify, or restart the search.

4.5.2. Initial solution generation

Due to the amount of constraints that are taken up in the model, a feasible solution is not simply found by selecting a random set of p vertiports and checking whether or not it results in a feasible network. Therefore, an algorithm to find a feasible initial solution is proposed, as shown in Fig. 5. The algorithm aims to construct a feasible set of vertiports by first randomly selecting a vertiport that is in the maximum safety distance range of a heliport, after which candidate vertiports are selected and only added if they adhere to the constraints. A runtime restart is added to prevent the algorithm from running infinitely in case no feasible vertiport can be added to the constructed solution. If this is the case, the solution that is constructed so far is deleted and the algorithm starts with the construction of a completely new solution.

4.5.3. Neighborhood structure

The proposed TSA searches the solution space by checking a set number of solutions in the neighborhood of the current optimal solution. As, for this specific problem, a solution consists of a set of p feasible vertiport locations, the neighborhood can be constructed by making a small adjustment to the current solution. Similar to the work of Skorin-Kapov and Skorin-Kapov (Skorin-Kapov and Skorin-Kapov, 1995), a neighboring solution is defined to be any feasible solution whose set of vertiports differs in exactly one node from the set of vertiports of the current solution. Additionally, to prevent duplicate solutions, for the complete neighborhood, a constraint is added that ensures no two solutions in the neighborhood may consist of exactly the same set of vertiports.

4.5.4. Algorithm moves & overview

To search the solution space efficiently, the algorithm is able to perform three types of moves: intensification, diversification, and restart. Each one is performed when a user specified value of the local iteration counter i_{local} is reached. The local iteration counter is reset when a new solution is added to the MTM, indicating that the part of the solution space that is currently being exploited yields promising solutions. If no new solution is added to the MTM, the local iteration counter updates its value. The first type of move that is activated by the local iteration counter is the intensification. At each iteration, the objective scores of each of the solutions in the neighborhood are computed.

More than one of the solutions in the neighborhood may be Pareto equivalent due to the model having multiple objectives. Of these found optimal solutions, one is selected to be added to the MTM and accepted as the new current solution which the algorithm moves on with. However, it is a waste to discard the other Pareto equivalent solutions. These are stored in the IM and used for the intensification move. After a set amount of local search iterations yielding no better solutions or Pareto equivalent solutions as compared to the ones that are currently stored in the MTM, an intensification move is performed. This entails, randomly selecting one of the points stored in the IM and using it as the new current solution. This results in a search in an area that seemed promising at an earlier stage in the search.

If the intensification yields no promising solutions, a diversification is performed. This is done to search for new promising areas in the solution space. For the diversification move, the algorithm selects a new random point in the solution space and continues to search in the neighborhood of this new solution to escape from local optima. In the case that the diversification does not provide promising solutions after a set amount of local iterations, a restart move is performed, meaning that the algorithm returns to one of the solutions in the MTM and continues its search in that part of the solution space. Finally, if no better solutions than the current are found in the neighborhood and the local iteration counter does not trigger an intensification, diversification or restart, one of the neighborhood solutions is randomly selected as the next current solution. This is referred to as a downhill move which helps to escape local optima. To provide a clear overview, a flowchart diagram of the used adapted multi-objective TS algorithm is shown in Fig. 6.

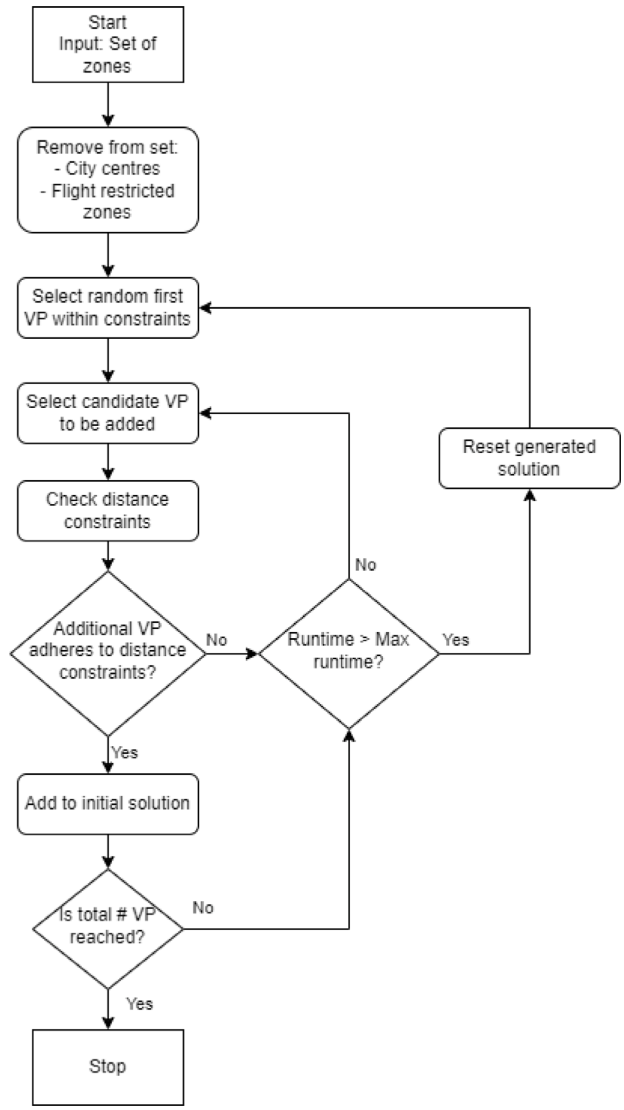


Fig. 5. Initial solution generation algorithm.

5. Case description: South Holland region

The South Holland region was chosen for several reasons. First, it has the largest population of all provinces in the Netherlands with about 3.8 million inhabitants. Naturally, this results in a high demand for packages making it an interesting region to implement an MMD system in. Furthermore, South Holland presents a complex urban environment that contains both large cities with tall buildings as well as flatter areas of land and industrial areas such as the Maasvlakte.

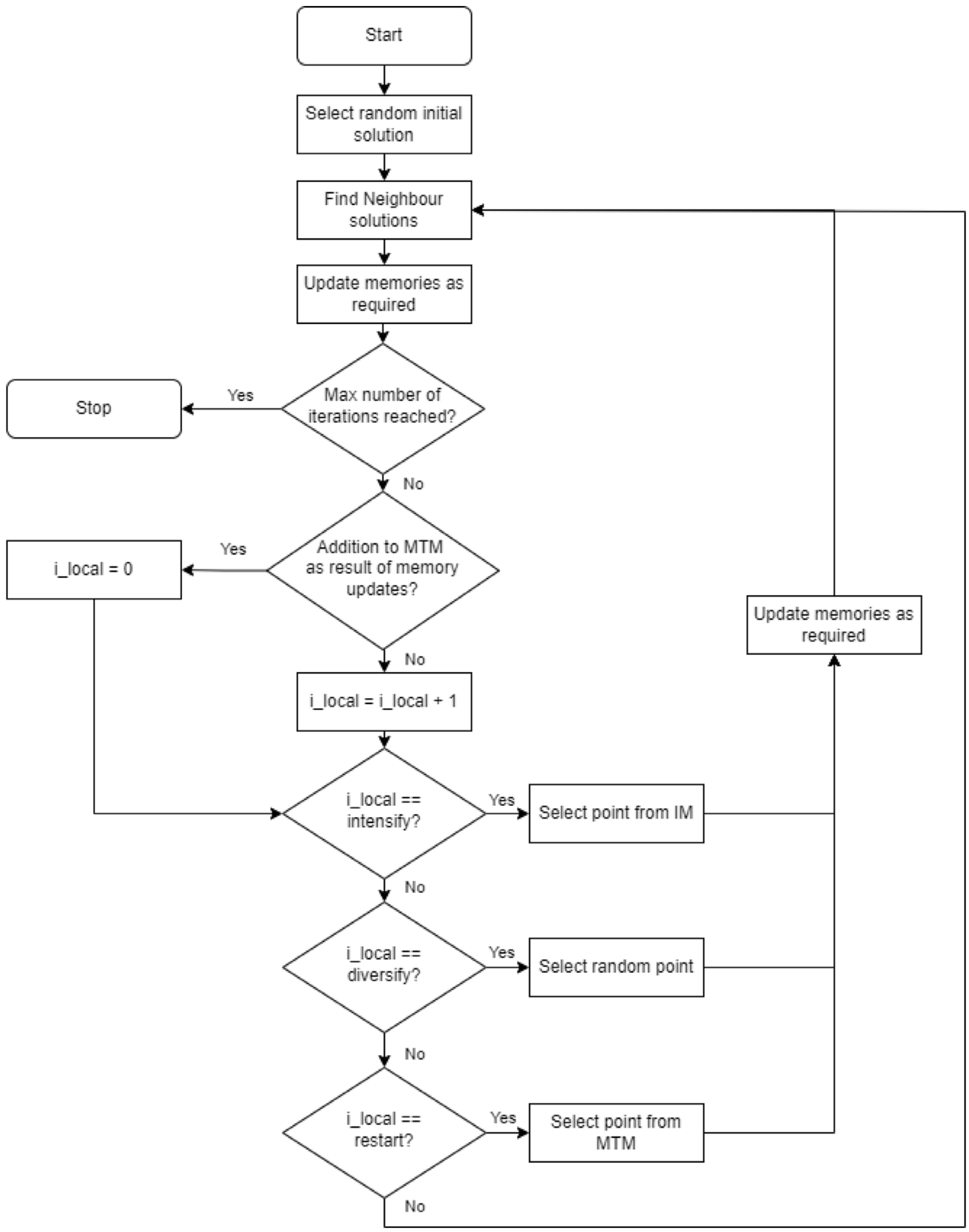


Fig. 6. Adapted Multi-Objective Tabu Search Algorithm (Jaeggi et al., 2008).

Moreover, the port of Rotterdam is working on the implementation of a U-space airspace (Port of Rotterdam, 2023), enhancing the interest of an MMD concept using UAM in the area of Rotterdam. Finally, data on the demand for packages is readily available in the South Holland region through the release of the Mass-GT model (de Bok and Tavasszy, 2018). The latter contains a division of the study area into a number of 6625 zones, and 29 warehouses from several parcel delivery operators in the Netherlands. The combined demand of all warehouses is 242866 packages for a single day in 2016, which are divided up into an amount of 30168 origin–destination pairs with each their own demand value. Analogously to other cities, the selected case study imposes several constraints:

- Flight restrictions: The Dutch government has a set of restricted flight zones for the usage of drones. This is an aspect that should be considered when selecting suitable locations for vertiports. One major flight restricted area is caused by the presence of Rotterdam The Hague Airport (RTHA). Within the control zone of the airport, no drone flight is permitted. As this control zone covers most of the South Holland region containing high demand, it is assumed that arrangements can be made with RTHA to permit drone flight within this zone. Nevertheless, the South Holland region also contains restricted flight zones due to the presence of vital infrastructure and existing heliports. These flight restrictions are taken up in the model, constraining the feasible solution space.
- Availability infrastructure space: A basic assessment is made of each of the 6625 zones using aerial pictures. The resulting estimated area is categorized into four categories being: no space, a small amount of space, a large amount of space and a very large amount of space. This is, in turn, used for capacity estimations.
- The city center of Rotterdam and The Hague, which are the two most populous cities in the province of South Holland. The constant presence of a large amount of people in these two city centers causes an increase in the risk of casualties in case of

Table 1
Base settings used for experiments.

Input	Value
Number of clusters K	1000
Number of vertiports p	25
Drone range	30 [km]
Maximum Safety Distance	10 [km]
TAT	20 [min]

emergencies. Therefore, these areas are deemed as not being suitable for the placement of vertiports and introduce a constraint to the model.

6. Experimental setup

In this section, the experimental setup for our case study is described. First, in Sections 6.1 and 6.2, the independent variables and control variables are defined, respectively. This is followed by a description of the five experiments that are performed in Sections 6.3 to 6.7.

6.1. Independent variables

As a setup for the experiments, the following independent variables are selected and varied during the experiments:

- **Cluster amount K**: The number of clusters that are used in the K-means algorithm. Three different amounts of clusters are used: 500, 1000, and 2000.
- **Amount of vertiports**: The exact number of vertiports that are placed to construct the UAM network. Four different vertiport amounts are used: 10, 25, 50, and 100.
- **Drone range**: The range that drones can fly from a warehouse to the destination vertiport. Four different drone ranges are used: 20, 30, 40, and 50 km.
- **Maximum safety distance**: The maximum distance between vertiports, or between a vertiport and an existing heliport, to accommodate for diversions in emergency situations. Four maximum safety distances are used: 5, 10, 15, and 20 km.
- **Turn around time (TAT)**: The turn around time of a drone landing at a vertiport, for dropping of its payload and recharging or swapping batteries. Four values of TAT are considered: 5, 10, 15, and 20 min.

6.2. Base settings and control variables

For the experimental setup, the base scenario and several control variables are defined. The base settings of the independent variables are shown in Table 1. The drone range is based on the Draganfly Heavy Lift cargo drone which has a range of 30 km and a maximum payload of 30 kg. This drone is chosen as it is readily available and has a relatively high payload capacity. In terms of flight range, the drone has a medium performance as compared to other drones with lower payload capacities. While there are drones that can fly for around 60 km such as the Blowfish A2G (Ziyan UAS, 2023), these drones offer far lower payload capacities which might not be optimal for an MMD concept. Furthermore, for the TAT, the worst-case scenario is assumed resulting from found values for eVTOL-based operations in existing literature (Preis et al., 2021). This resulted in a TAT of 20 min. Furthermore, it should be noted that the same initial solution is taken for all experiments. As the initial solution determines the starting point in the solution space, each experiment is then set to start searching at the same location. This is done to negate the effects of sensitivity of the framework to the initial solution.

Table 2 shows the physical control variables and their respective values. The minimum safety distance is based on the approach/departure surface specified by the heliport design and prototype vertiport design specifications of EASA (European Union Aviation Safety Agency (EASA), 2019; Anon, 2021). Similarly, the minimal available airspace is also based on these specifications, which state that both the approach and the departure surfaces must be 1220 meters long and have a width of 152 m, therefore, resulting in a total needed area of 0.37088 [km^2]. Furthermore, an average package weight of 2.5 [kg] is assumed resulting in a drone capacity of 12 packages. Moreover, the hours of operations of the UAM network are assumed to be the same as regular working hours: from 9:00 to 17:00. Following these assumptions capacity estimations were made for the vertiports. These estimations are based on the amount of drones a vertiport is able to handle throughout the span of one day. As a drone is set to have a capacity of 12 packages, the capacity of a vertiport is determined by multiplying the maximum amount of drones a vertiport can handle by the drone capacity. For small, medium and large vertiports, the vertiports are assumed to be consisting of 1, 4, and 16 pads, respectively. This results in the capacities shown in Table 2.

Table 2
Physical control variables.

Input	Value
Minimum Safety Distance	2440 [m]
Maximum Last Mile Distance	10 [km]
Minimal available airspace	0.37088 [km^2]
Maximum cluster area	100 [km^2]
Max drone payload	30 [kg]
Drone capacity	12 packages
Vertiport working hours	9:00–17:00
Capacity of small vertiport Γ_{small}	288 packages/day
Capacity of medium vertiport Γ_{medium}	1152 packages/day
Capacity of large vertiport Γ_{large}	4608 packages/day

Table 3
Tabu Search Algorithm control variables.

Input	Value
Neighborhood size	50
STM size	150
Number of TS iterations	4000
Value of local iteration counter i_{local} for intensification	10
Value of local iteration counter i_{local} for diversification	15
Value of local iteration counter i_{local} for restart	50

Finally, Table 3 shows the control variables related to the TS algorithm. The neighborhood size determines the amount of solutions that are generated and tested at each iteration. An increase in the neighborhood size results in searching a larger part of the solution space. While this seems beneficial, the neighborhood size is limited by the computational power that is available. The STM size is set to be three times the size of the neighborhood, to prevent the algorithm from returning to recently visited points for at least three iterations. This is done to ensure that the algorithm keeps exploring new parts of the solution space. Furthermore, each of the experiments is run for 4000 iterations due to computational limitations. The combination of 4000 iterations with a neighborhood size of 50 results in testing 200.000 solutions. This is deemed to be sufficient to result in reasonable quality of results to identify relations between the independent variables and the model objectives as the results tend to stabilize when further increasing the number of iterations. Running the model with 6000 iterations showed no significant differences in terms of the solutions and relations found. Finally, i_{local} intensify, diversify and restart describe at which value of the local iteration counter i_{local} the algorithm performs an intensification, diversification or restart move.

6.3. Experiment A: Amount of clusters K

The first experiment relates to the selection of the amount of clusters K in the K-means algorithm. Varying the amount of clusters in the

K-means algorithm has the benefit of being able to make a trade-off between detail and computational efficiency. As the HLP that is considered has a very large solution space compared to other HLP problems, it is computationally beneficial to reduce this solution space by simplifying the problem to get faster results. However, reducing the number of clusters comes at the cost of losing detail with respect to selecting suitable zones, as a single vertiport is then considered to cover a larger area of land. As a result, the ability to select a very specific area as vertiport location is lost. It is expected that this will also lead to a decrease in safety and noise performance as these factors are now rated over a larger area. Therefore, detail is also lost in the fact that the algorithm is not able to pick very specific areas that perform particularly well in terms of safety and noise nuisance. In terms of demand, while this is also clustered, due to the warm start solution most areas containing high demand will still have a large number of zones present and therefore candidate vertiport locations. It is therefore expected, that varying the amount of clusters will not have a large impact on the demand that can be served. This first experiment aims to select a suitable amount of clusters by making a trade-off between the detail (the highest level of detail is preferred) and the computation time that it takes to run an experiment for the set level of clusters. This is tested using 500, 1000, and 2000 clusters. The following hypotheses are set:

- H_{A1}: An increase in the amount of clusters will have a negligible effect on the demand that can be served.
- H_{A2}: An increase in the amount of clusters will improve safety scoring.
- H_{A3}: An increase in the amount of clusters will improve noise scoring.

6.4. Experiment B: Amount of vertiports

The second experiment relates to the selection of the amount of vertiports that are placed to construct the UAM network. While the proposed framework does not consider the cost of operating or building vertiports, in reality, this factor will have a large influence on the implementation of the network. For a larger number of vertiports, the construction and operating costs will be higher. A useful insight that the proposed framework may provide is therefore to look at the relation between the amount of vertiports that are placed and the demand that could be served with such a network. This can help with the decision of whether or not it is worth to implement an MMD UAM network with a select amount of vertiports. Furthermore, having to place a larger amount of vertiports, will also influence the noise and safety scores as the model might have to resort to placing vertiports in zones that do not perform well in terms of safety and noise. Therefore, it is expected that an increase in vertiports will result in worse performing networks in terms of safety and noise. The influence of the vertiport amount on these factors is tested using 10, 25, 50, and 100 vertiports. The following hypotheses are tested:

- H_{B1}: An increase in the amount of vertiports will increase the demand that can be served.
- H_{B2}: An increase in the amount of vertiports will worsen safety scoring.
- H_{B3}: An increase in the amount of vertiports will worsen noise scoring.

6.5. Experiment C: Drone range

The third experiment takes the drone range as the variable of interest. For the base scenario, the draganfly heavy lift drone is used, which has a range of 30 [km]. The effectiveness of a UAM network is largely influenced by the drone range as with a smaller drone range, less remote areas can be reached and vertiports will have to be placed closer to the origin locations. Therefore, it is expected that a higher demand coverage can be obtained for an increase in drone range. Additionally, lower drone ranges restrict the model from finding locations that are more suitable in terms of safety and noise. As a result, it is expected that increasing the drone range will lead to improved solutions in terms of safety and noise. While the base scenario takes an existing drone, future innovations will likely lead to the ability to use drones with higher ranges. The aim of this experiment is therefore to see the effect of an enhanced range on vertiport placement. Furthermore, a lower value of range is also tested to see the influence of selecting a drone with a smaller range, which might be cheaper. For the experiment, four values of drone range will be tested: 20, 30, 40, and 50 [km]. The following hypotheses are tested:

- H_{C1}: An increase in the range that drones can fly will increase the overall demand that can be served.
- H_{C2}: An increase in the range that drones can fly will improve the safety scoring.
- H_{C3}: An increase in the range that drones can fly will improve the noise scoring.

6.6. Experiment D: Maximum safety distance

The maximum safety distance between vertiports is of the essence to provide safe diversion possibilities in case of emergencies. With safety being the main public concern when it comes to implementing a UAM network (European Union Aviation Safety Agency (EASA), 2021), this metric is of great interest. While a minimum safety distance between vertiports can be concluded from the vertiport design specification prototype (Anon, 2021), there is no given maximum safety distance. As it is expected that regulations on the maximum safety distance will be set for the design of a UAM network, it is of interest to analyze the effect that this distance has on the network. Having a lower maximum safety distance is expected to result in a denser network of vertiports, which in turn could have a negative effect on the demand served, noise, and safety score. In terms of model performance, a lower safety distance results in a more constrained problem, making the solution space smaller which might result in more computation time due to the fact that it is harder to construct feasible solutions. The effects of varying the maximum safety distance are tested for four distances: 5, 10, 15, and 20 [km]. The following hypotheses are tested:

- H_{D1}: An increase in maximum safety distance will increase the demand that can be served.
- H_{D2}: An increase in maximum safety distance will improve safety scoring.
- H_{D3}: An increase in maximum safety distance will improve noise scoring

6.7. Experiment E: Turn around time (TAT)

The fifth experiment relates to the TAT of drones after arrival at the destination vertiport. This mainly affects the vertiport's maximum capacity and therefore the demand that can be served. This is of interest as it provides insights into the added benefits of optimizing ground processes. This could aid in decision-making on investments to improve ground operations at vertiports. For the experiment, four different values of TAT were taken, being 5, 10, 15, and 20 min, respectively. The following hypotheses are tested:

- H_{E1}: An increase in turn around time will decrease the demand that can be served.
- H_{E2}: An increase in turn around time will have a negligible impact on safety scoring.
- H_{E3}: An increase in turn around time will have a negligible impact on noise scoring.

7. Results

This section is divided into five subsections with each one presenting the results of a single experiment.

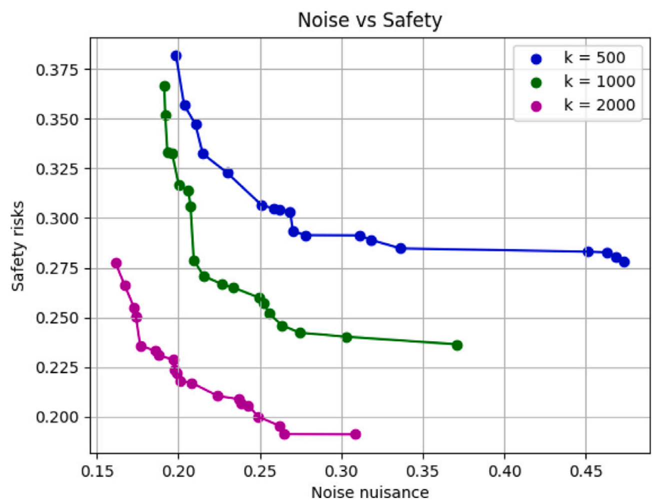


Fig. 7. Paretofronts of Experiment A only considering Safety and Noise.

7.1. Experiment A: Amount of clusters K

The aim of the first experiment is to select a suitable amount of clusters K to group the total of 6625 zones into of the South Holland region. This breaks down to a trade-off between the computation time that is required versus the level of detail that is used for the optimization. It was found that the resulting Pareto fronts are very similar in behavior, however, they are shifted with respect to safety and noise. This is best illustrated by plotting the Pareto fronts considering noise and safety as shown in Section 3. Fig. 7 shows that, in general, a higher number of clusters causes better safety and noise scores, resulting in a downward left shift of the Pareto front. This trend can be attributed to the fact that a lower amount of clusters results in more generalized noise and safety scores for each zone. This means that there will be fewer zones scoring very well on these factors and that the average noise and safety score for zones is higher.

Fig. 8 shows that a higher number of clusters results in significantly larger computation times. Experiments should be run with the highest number of clusters possible to obtain maximum detail.

Finally, Fig. 9 shows boxplots of all objective values that are stored in the Pareto front for the demand, safety and noise objectives, respectively. The found demand scores behave somewhat similarly in the sense that the best found value of demand is the same for all three values of K. In contrast, the worst accepted demand value differs throughout the different cluster amounts which is a result of the difference in obtained safety and noise scores. The amount of clusters strongly affects the optimal safety scores found in the Pareto front. While a similar relation can be argued for the noise scores, this relation is less strong. This can be explained by the fact that the safety score consists of three factors that are generalized while only one factor is considered for the noise scoring. As a result, the clustering process will have a larger effect on the safety scores.

7.2. Experiment B: Amount of vertiports

The second experiment relates to the impact of changing the amount of vertiports with respect to the objective scores as well as the computational effort. The resulting Pareto fronts that are found are shown in Fig. 10. The best score found per objective can be seen in Table 4. There is a strong relation between the amount of vertiports and the demand served. Whereas, with a total of 10 vertiports, 81% of all package demand cannot be served, this total decreases drastically as more vertiports are placed. The system not being able to serve only 9.8% of all package requests when using 100 vertiports. This is expected since

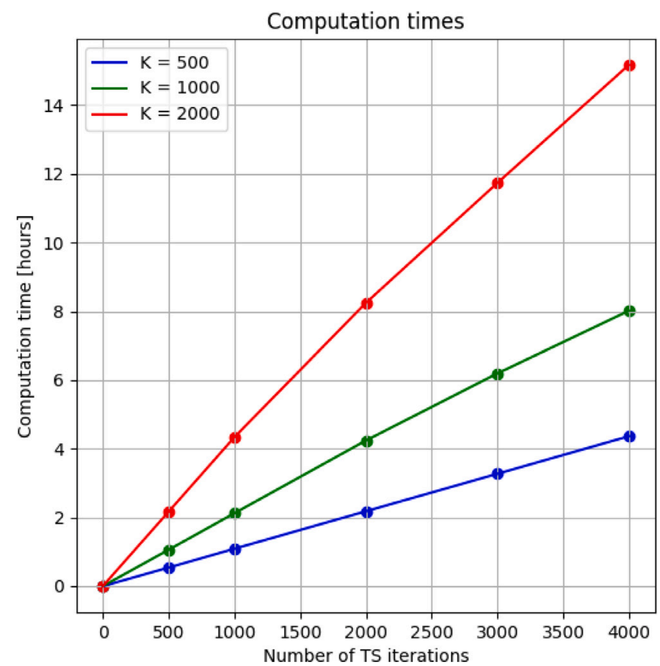


Fig. 8. Computation times as a function of iterations.

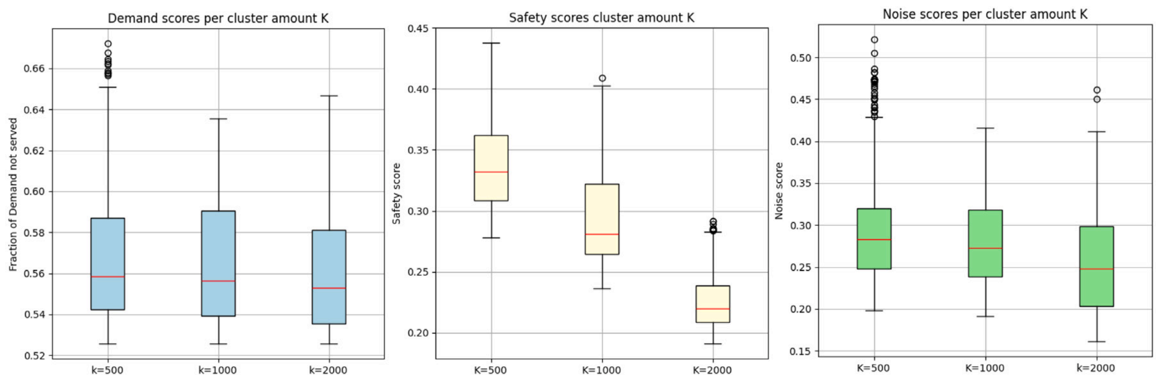
Table 4
Best score found per objective.

	Demand not served	Safety risks	Noise nuisance
10 VP's	81.0%	0.134	0.087
25 VP's	52.6%	0.236	0.191
50 VP's	17.7%	0.310	0.262
100 VP's	9.8%	0.354	0.320

a network containing more vertiports will be able to reach more areas and has a higher total capacity. Furthermore, it is observed that the best solutions in terms of safety risks and noise nuisance, degrade linearly with an increase in demand coverage as caused by the increase in the number of vertiports.

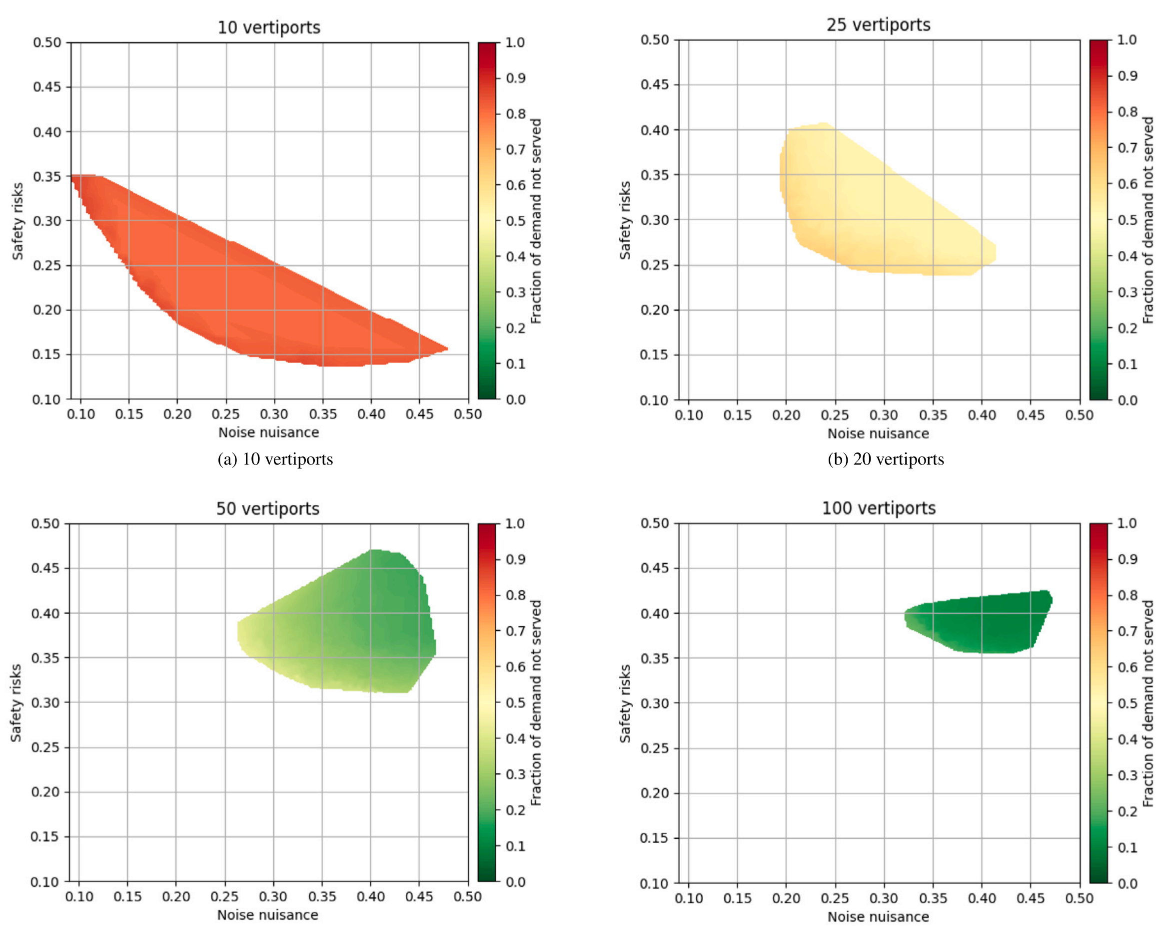
Furthermore, with an increase in vertiports, the model tends to find more Pareto equivalent solutions that score very well in terms of demand, however, a lot worse in safety and noise. This is indicated by the upward right shift of the Pareto front as the number of vertiports increases. With an increase in vertiports, the model is forced to pick some locations that perform worse in terms of these objectives. In combination with the fact that the increase in vertiports opens up the model to finding more solutions that score very well in terms of demand, this results in an expansion of the Pareto front towards networks that have a high percentage of demand served. In general, the zones that are selected often in solutions for a smaller amount of vertiports, are also selected often when increasing the amount of vertiports. Therefore, the increase of the number of vertiports results in an expansion from existing networks that are found for a small amount of vertiports instead of finding completely different solutions. Additionally, it is found that the zones that are often are centered around areas that contain a particularly high demand: the South East, North East, and near large cities.

Fig. 11 shows a drop-off for noise and demand scores with an increased amount of vertiports. Next to the negative correlation between the amount of vertiports and safety and noise scores, it is also visible that the Nadir points on the Pareto front, which are the two outer points, move towards each other as the number of vertiports increases. This indicates a reduction in variability between the found solutions in terms of noise and safety scores. An increased amount of vertiports



(a) Fraction of demand not served (b) Safety (c) Noise

Fig. 9. Boxplot of collected objective score from the Pareto front.



(a) 10 vertiports (b) 20 vertiports

(c) 50 vertiports (d) 100 vertiports

Fig. 10. Pareto front considering a UAM network with different number of vertiports.

results in a smaller solution space and noise and safety scores that are naturally closer together.

7.3. Experiment C: Drone range

The third experiment relates to the drone fly range from a warehouse to the destination vertiport. This is a one-way distance as it is assumed that the drone either receives a battery swap or is recharged at the destination vertiport. Fig. 12 shows the Pareto fronts that are found for variable drone ranges. A lower drone range generally results in a higher spread of the objective scores for given solutions. This indicates that for a smaller range, a harder decision has to be made on what objective is seen as most important when selecting a set of vertiports as the trade-off between objective scores is steeper. Although there is little difference in the optimal values achieved for each individual objective, the model is able to find a better combination of objective scores if the range is larger. Furthermore, there is a general downward left shift of the Pareto front as the range increases, indicating that better safety and noise scores can be obtained for larger ranges. Both of these results make sense as a larger range relieves model constraints. This results in the potential for better performing UAM networks.

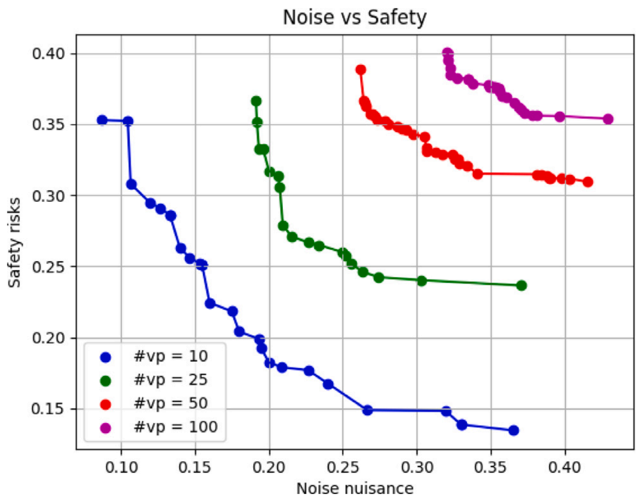


Fig. 11. Paretofronts of Experiment B only considering Safety and Noise.

According to Fig. 13, there are clear improvements in all scores as the range increases. Furthermore, while there is no significant difference between the demand scores found for the ranges of 40 and 50 km, there are significant differences between the safety and noise scores for these ranges.

7.4. Experiment D: Maximum safety distance

Experiment D aims to find the relation between the maximum safety distance and the objective scores. Fig. 14 shows that, while the best demand scores are similar for all four settings, there is a slight increase in terms of safety and noise for some of the solutions found when increasing the maximum safety distance. This is indicated by the downward left extension of the Pareto front. Additionally, there is no clear improvement in terms of safety and noise for the entire Pareto front. This is best illustrated by Fig. 15, which shows the Pareto fronts when just considering safety and noise scores. With a maximum safety distance of only 5 km, the solutions that were found perform worse in both safety and noise as it is shifted upward right. In contrast, for the other three distances, there is no overall improvement of the Pareto front in terms of the safety and noise objectives. Nevertheless, there are some improvements when increasing the maximum safety distance. This results in having to make a more impactful decision on preference between objective scores when selecting a set of vertiports to implement as the trade-off is steeper.

Fig. 16 shows that an increase in maximum safety distance does not directly increase the served demand. However, worse demand scores are accepted by the framework more often as viable solutions due to the improvements in safety and noise. As a result, no clear conclusion can be made on the influence of the varying maximum safety distance on the served demand.

7.5. Experiment E: Turn around time

Experiment E assesses the relation between a varying TAT and the objective scores as well as the computation time. The Pareto fronts, in Fig. 17, extend in an upward right fashion as the TAT decreases. With a lower TAT, better demand scores can be obtained, resulting in the acceptance of worse safety and noise scores. Furthermore, the demand score increases drastically with a decrease in TAT.

Finally, Fig. 18 shows that, for a higher TAT, the fraction of demand not served increases significantly, not only in best obtained value but also in median.

8. Discussion

This section discusses the developed framework and its implementation. Through the performed experiments, it was demonstrated that the framework is able to identify several relations between a number of independent variables and KPIs, namely network demand coverage, safety risks, and noise nuisance. The results show that there is often an opposing balance between responding to demand and acceptable noise and safety levels. Serving a higher level of demand is often associated with placing vertiports in densely populated areas, which worsens the total noise and safety impact of the vertiport network.

While the tool was applied to the South Holland region, it may be used for any city or region for which the necessary data can be acquired. The optimal vertiport locations it identifies can serve as guidelines for designing a vertiport network that maximizes demand coverage while adhering to safety and noise regulations. Finally, the Pareto front output will assist users in balancing various objectives effectively.

This section is divided into three subsections. First, confirmation of the hypotheses identified in Section 6 is discussed in Section 8.1. This is followed by a discussion of how the model is affected by some of the assumptions that were made in Section 8.2. Finally, the section is concluded by discussing the limitations of the developed framework in Section 8.3.

8.1. Validity of hypotheses

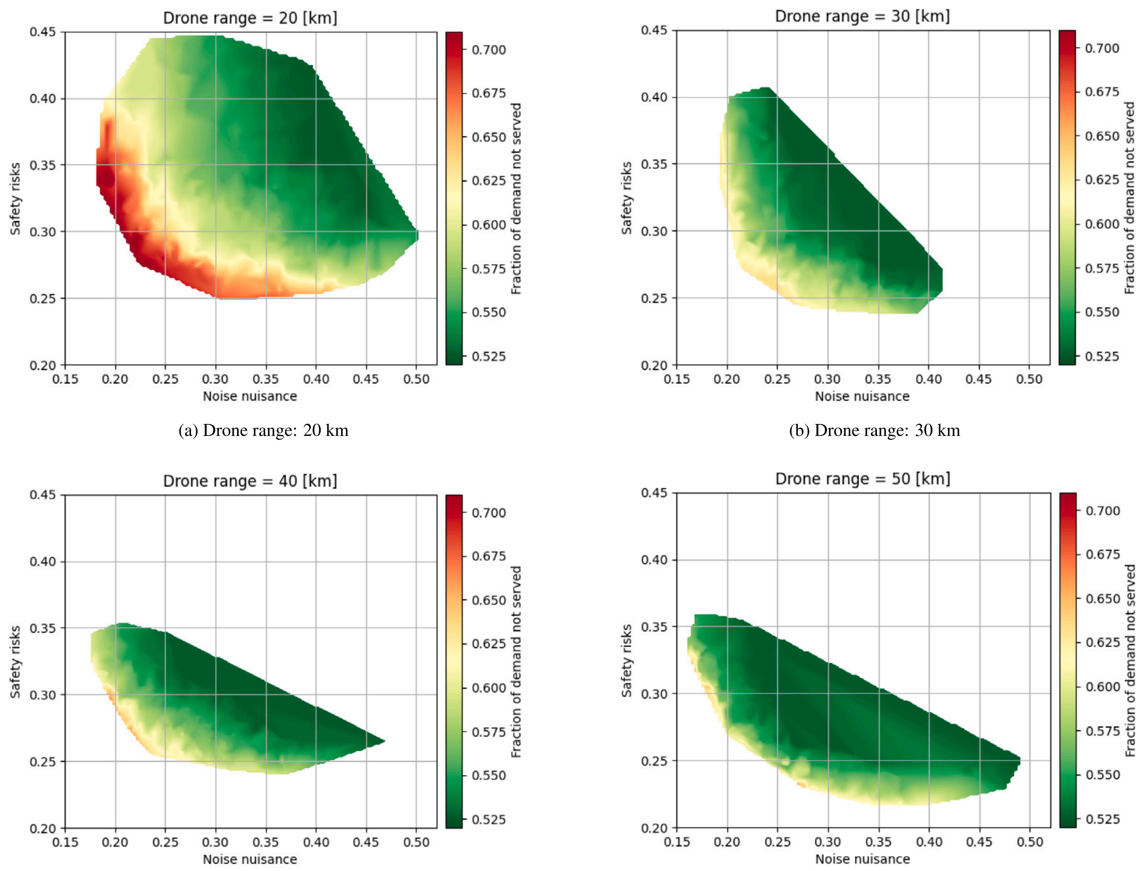
Experiment A, focusing the suitable number of zone clusters, identified that the number of vertiports did not considerably affect the demand not served, therefore, H_{A1} is rejected. H_{A2} and H_{A3} are both accepted as, with more clusters, the framework was able to find solutions that perform better both in the safety or noise objectives. Overall, increasing the number of clusters allows the framework to better select specific areas with better conditions for the vertiport network.

Regarding Experiment B, analyzing the impact of the amount of vertiports, H_{B1}, H_{B2}, and H_{B3} are all accepted. Increasing the number of vertiports will logically increase the served demand, but will likely worsen safety and noise as more non-optimal locations are used to build the more extensive network.

Regarding the effects of the drone range in experiment C, hypotheses H_{C1}, H_{C2}, and H_{C3} are all accepted. The impact of varying the drone range is positively significant for all three objectives: demand served, safety, and noise.

From the obtained results of experiment D on the maximum safety distance, it is not possible to accept hypothesis H_{D1} as no improvements of the demand objective are found while increasing the maximum safety distance. Moreover, the obtained best solutions in terms of demand show very similar demand scores. The lack of improvement in demand scores could be a consequence of capacity limitations of the UAM network. Therefore hypothesis H_{D1} is also not rejected. For safety and noise, while the overall Pareto front does not necessarily shift, a significant improvement in best safety and noise scores was observed as a result of increasing the maximum safety distance. Therefore, hypotheses H_{D2} and H_{D3} are accepted.

Finally, regarding TAT in experiment E, hypothesis H_{E1} is accepted — an increase in TAT negatively affects the served demand. In turn, hypotheses H_{E2} and H_{E3} cannot definitively be accepted or rejected. Noise and safety scores do not have a strong reaction to the TAT as the found solutions contain similar scores. Nevertheless, there are changes that can be attributed to the acceptance of solutions that score particularly well on demand which indirectly affect noise and safety scoring.



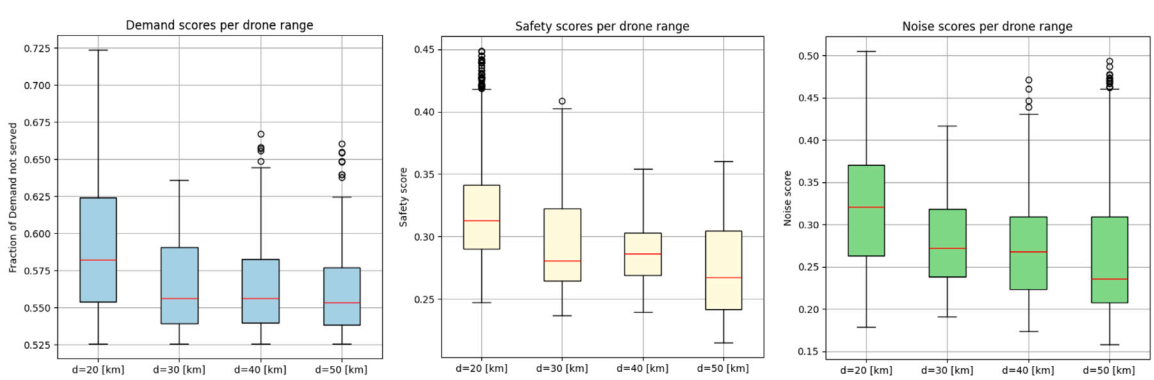
(a) Drone range: 20 km

(b) Drone range: 30 km

(c) Drone range: 40 km

(d) Drone range: 50 km

Fig. 12. Pareto front considering a UAM network with different drone range.



(a) Fraction of demand not served

(b) Safety

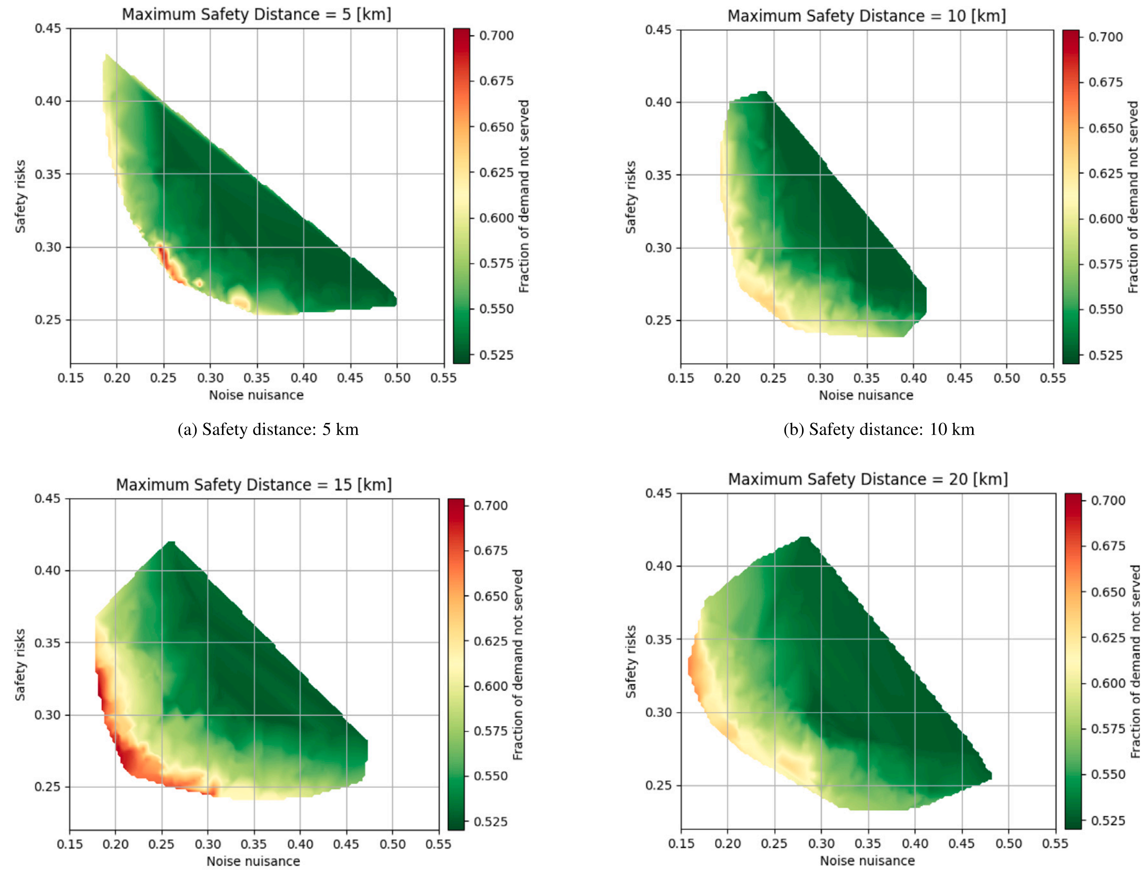
(c) Noise

Fig. 13. Boxplot of collected objective scores from the Pareto front.

8.2. Assumptions

There are a number of assumptions that could have an influence on the frameworks' performance and solutions. First, for the performed experiments, 4000 iterations of the Tabu Search algorithm were performed. In each of these iterations, 50 solutions were checked, resulting in a total of 200.000 possible solutions being tested, which is in the order of 10^5. If a total of 25 vertiports are selected out of 1000 locations (as is the case for the base scenario), the solution space is roughly of the size 10^{50}. Due to the large amount of constraints that are introduced in the framework, the feasible solution space will be a lot smaller. Nevertheless, we are still only checking a relatively small portion of the total amount of solutions. Therefore, it cannot be guaranteed that the absolute optimal solutions are obtained. In real-life applications, the model should be run for a larger amount of iterations to obtain results of higher quality. Additionally, this phenomenon also causes the framework to have some sensitivity to the initial solution that is inputted. It is recommended to run the framework for as many iterations as possible with a large neighborhood, subject to limitations on time and computational power, in order to negate these effects.

Additionally, while 200.000 solutions and 4000 iterations were deemed sufficient for this case scenario, it is likely that larger or more complex networks will require more computational effort. To be noted that, in broader scenarios, due to the larger set of feasible solution space, the framework may be more sensitive to local optima. Such should be considered in future larger scale studies. The number of



(a) Safety distance: 5 km

(b) Safety distance: 10 km

(c) Safety distance: 15 km

(d) Safety distance: 20 km

Fig. 14. Pareto front considering a UAM network with different maximum safety distance.

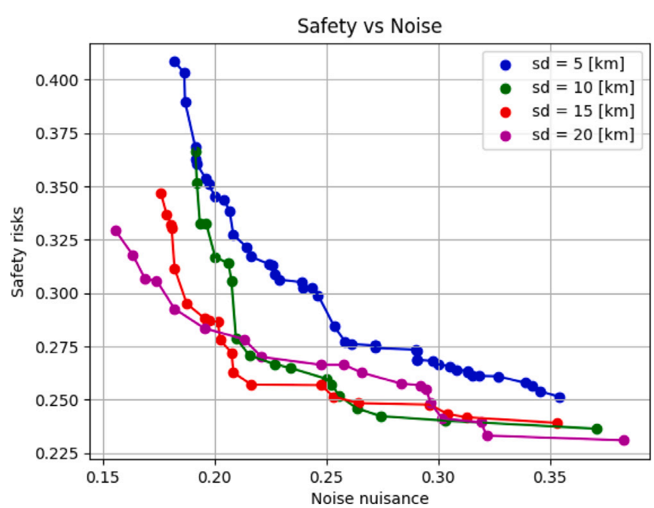


Fig. 15. Paretofronts of Experiment D only considering Safety and Noise.

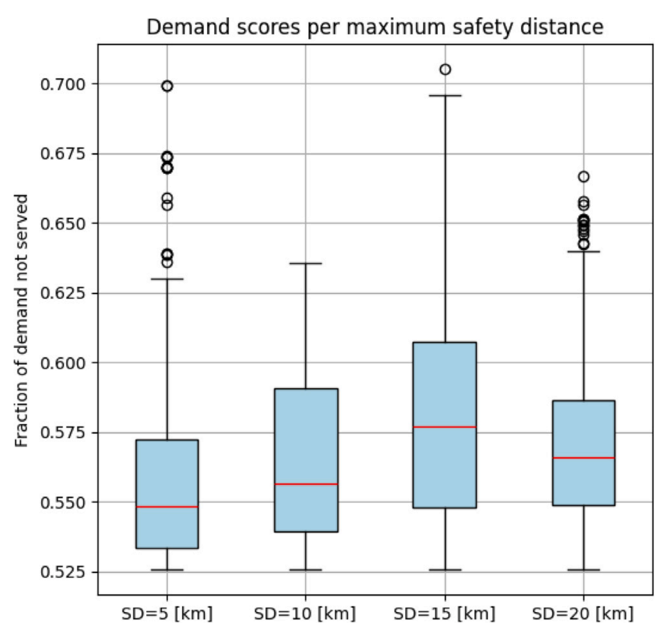


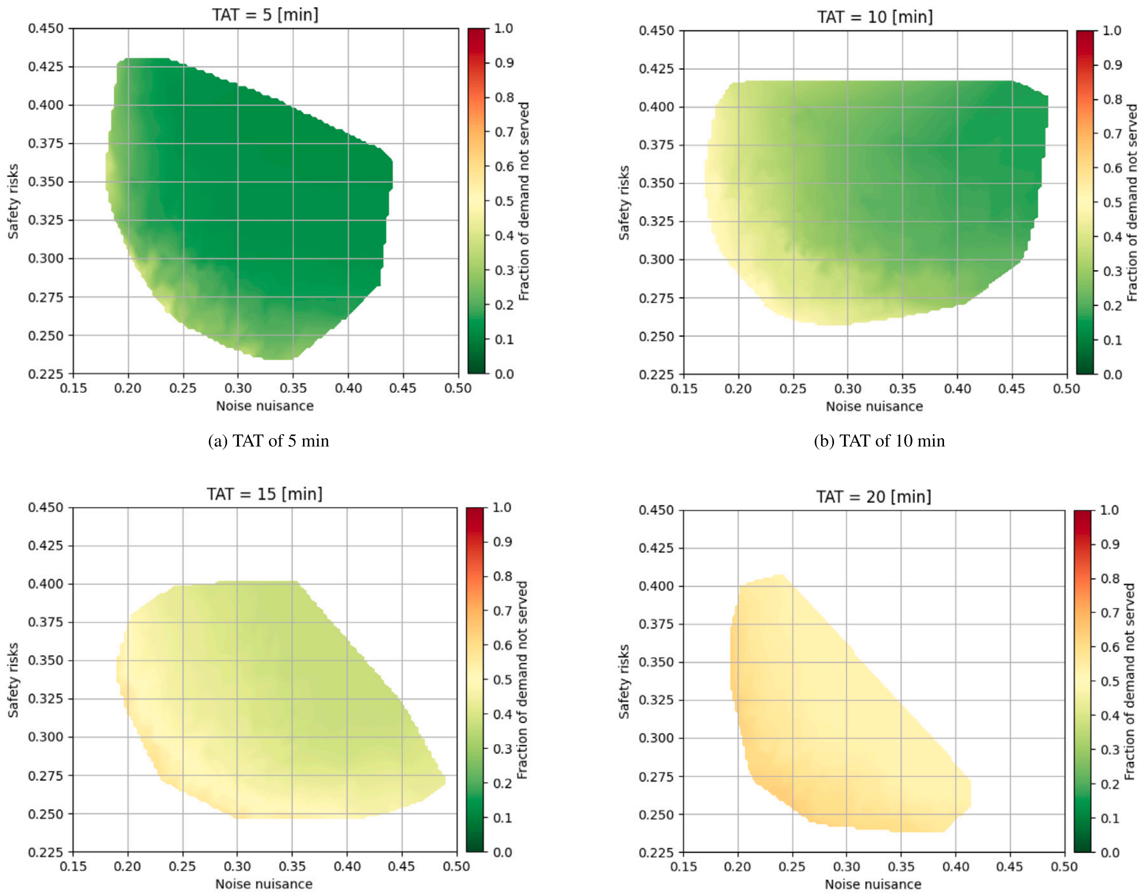
Fig. 16. Boxplot of collected demand objective scores from the Pareto front.

iterations in this study should not be taken as a guideline for all studies.

Finally, the framework assumes that the vertiport is located at the geographical centroid of the zone. This location is used for any distance constraints and calculations. As the maximum area of a zone is set to be of size 100 km^2, the real location of the vertiport could differ from the centroid by a few kilometers, depending on the shape of the zone. As this might affect parameters such as the necessary drone range, this should be considered when selecting vertiport locations and drone type.

8.3. Limitations

While the framework is able to provide interesting insights into vertiport positioning, there are some limitations to the model that



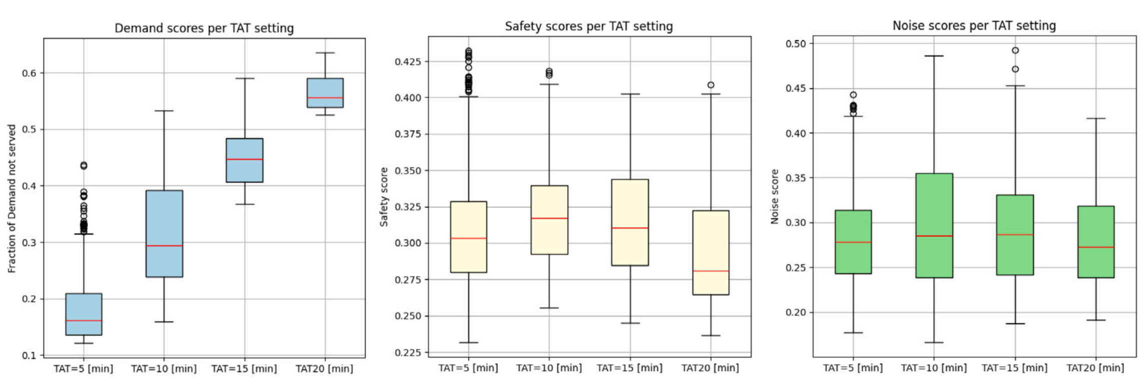
(a) TAT of 5 min

(b) TAT of 10 min

(c) TAT of 15 min

(d) TAT of 20 min

Fig. 17. Pareto front considering a UAM network with different TATs.



(a) Fraction of demand not served

(b) Safety

(c) Noise

Fig. 18. Boxplot of collected objective scores from the Pareto front.

should be noted. The first limitation is the high amount of unknowns about the implementation of UAM for MMD. For example, the capacity estimations that are made for a vertiport are quite basic due to limited available knowledge on drone operations for MMD. Furthermore, the identified relations between the independent variables and KPIs are based on estimated drone characteristics. As innovation within the heavy lift drone market occurs, drone characteristics might change significantly. In addition, future regulations on vertiport placement are currently not all known. The regulations that were implemented are based on the prototype design specifications of vertiports as published by EASA (Anon, 2021). This is still subject to change. While these unknowns, introduce some uncertainty in the obtained results, the framework can easily be adapted to changes by simply changing input parameters or adding constraints in case of regulation adaptations.

Another limitation of the framework is the considerably long runtime for exhaustive searching. As mentioned, searching a larger part of the solution space could result in the discovery of better performing networks. The downside of this is that the computational time increases linearly with the amount of tabu search iterations. This is a phenomenon to take note of in the case that there are time limitations on a project for which this framework is used, specially as the number of vertiports increases.

The results of the model should be interpreted in the context of its simplifications. First, a limited number of zones is analyzed to reduce computational time, which results in a loss of granularity when representing the diverse areas within the same zone. Additionally, the model assumes a homogeneous fleet, which does not represent the many performance differences between future stakeholders. As a result, the outcomes should be viewed as indicative of optimal vertiport locations, but the actual demand served may differ from the model's predictions. Finally, the managerial aspects of vertiport operations—such as scheduling, traffic flow management, and ground operations—are not included in the framework. Consequently, in real-world scenarios, the demand served may be lower than predicted, as traffic flow restrictions may be imposed for safety reasons.

8.4. Recommendations

Overall, the developed model provides a first basis for additional research to build upon as, currently, there exist no multi-objective models for a UAM MMD system considering multiple warehouses. Furthermore, the model can aid in the analysis of potential vertiport networks for decision-makers. The framework offers the possibility to assess the suitability of a region for the implementation of a UAM network for MMD. In addition, decision-makers can use the framework to decide upon investments and tune network performance. Furthermore, since the framework does not contain bias or preference towards any of the three objectives, it offers the ability for users to determine these preferences themselves and perform a trade-off.

It is recommended to extend the framework by including fleet size limitations, warehouse capacities, and budgetary constraints. These are factors that are not taken up in the framework but will play a large part in actual network development. Secondly, the framework could benefit from the introduction of more advanced safety and noise metrics. For example, for noise nuisance, the model can be extended to consider the effects of cumulative noise. Furthermore, it is recommended to implement a more advanced capacity model when more statistics on vertiport ground operations become known as this largely influences network performance. Finally, the demand request allocation algorithm could be extended to optimize for energy or time efficient routing.

For the optimization of larger networks, where the solution space grows significantly, a few recommendations are given. First, approaches to pruning the solution space, such as heuristic-guided neighborhood structures can positively impact computational speed by reducing the number of candidate solutions (Lai et al., 2021; Wang et al., 2024). Second, adaptive memory strategies can prevent cycles and enhance convergence speed (Alotaibi, 2022). Finally, parallel and distributed computing can significantly reduce computation time by enabling the simultaneous exploration of multiple solution regions.

Additionally, future work would benefit from considering a heterogeneous fleet of drones, entailing different performance compatibilities. This approach more accurately reflects the differences among vehicles used by different stakeholders. Consequently, factors such as payload capacity, range, and TAT would vary depending on the chosen vehicle. From a modeling perspective, this would involve running multiple models with distinct parameters, affecting travel times and demand served.

Finally, this work assumes static demand. In reality, demand is influenced by various geographic, political, and economic factors, and it can vary significantly over time. Nevertheless, users of this framework may lack reliable predictions of future demand. Therefore, this framework should be used to generate multiple solutions for different demand confidence intervals. Additionally, when accounting for demand uncertainty, future research may choose to compare the current approach with algorithms that can handle stochastic environments, such as approximate dynamic programming (Lee and Boomsma, 2022; Ulusan and Ergun, 2021), where the benefits of specific vertiport locations can be evaluated in a stochastic setting.

9. Conclusions

This paper presented a Multi-Objective Multiple Allocation Capacitated p-Hub Coverage Problem optimization model for the positioning of vertiports in a parcel delivery system where drones are used for the middle-mile segment of the transportation process. In this framework, parcels are transported from 29 warehouses to centrally placed vertiports that function as distribution centers. We proposed a Tabu Search based heuristic approach to solving the optimization problem due to the large size and complexity. Furthermore, an area constrained version of the K-means algorithm was presented to scale down the solution space and decrease computational efforts. The model serves as a basic framework to perform first analyses on the implementation of a Middle-Mile Delivery (MMD) Urban Air Mobility (UAM) network by identifying optimal locations for vertiports. The South Holland region was selected as a use case, however, the model is easily adapted to other areas.

The framework's ability to gain insight into the following decisions and the relations to the different objectives were demonstrated. First, the framework provides the options to assess the vertiport networks considering various amount of vertiports. Investing in a larger amount of vertiports enhances a network's demand coverage while introducing more safety risks and noise nuisance. Secondly, the work provides information on the effects of selecting different types of drones. Better performing drones, with a larger range, allow for networks that perform better in terms of demand coverage, safety risks and noise nuisance. Although the type of drone is largely determined by an operator's budgetary considerations and current technology, this work shows that investments in the innovation of drones can yield large benefits. Thirdly, introducing a maximum safety distance between vertiports or heliports was demonstrated to result in a steeper trade-off between the three objectives when selecting a viable network. This leaves decision-makers with a harder decision on preference between demand coverage, safety risks, and noise nuisance. Moreover, we demonstrated the benefits of increasing the efficiency of ground operations: the demand coverage can be increased from 55% to 85% by decreasing the turn around time from 20 to 5 min.

This work is the first of its kind in terms of a framework that can be used to identify potential vertiport networks and aids in decision-making on investments for UAM network. Nevertheless, there are still limitations connected to the uncertainties on future drone capabilities and regulations. Future work should focus on extending this framework with additional social-economic elements regarded by future UAM regulations.

CRediT authorship contribution statement

Victor Petit: Writing – original draft, Software, Methodology, Data curation. **Marta Ribeiro:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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