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Vertiport Infrastructure Location Optimization for Equitable Access to Urban Air Mobility

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Abstract: Urban air mobility (UAM) has recently emerged as a promising new transportation mode, with various potential use cases. Facility location problems are well studied and of significant importance for various transportation modes. This work introduces a vertiport location identification framework, focusing on demand coverage and infrastructure accessibility. An Agglomerative Hierarchical Clustering (AHC) model was utilized for the identification of candidate vertiport locations, along with a k-means algorithm, for comparison and validation purposes, based on an estimated UAM demand pattern. A genetic algorithm (GA) was then formulated, for the solution of the proposed Uncapacitated and Capacitated Vertiport Location Problems (UVLP and CVLP, respectively), variations of the Uncapacitated and Capacitated Facility Location Problems. To evaluate and compare the introduced methodology, different existing facility location problems (FLPs) were considered and solved exactly using integer and linear programming. These are the Location Set Covering Problem (LSCP), the Maximal Coverage Location Problem (MCLP), and the *p*-median problem. The *p*-center problem was also considered and solved via a heuristic approach. The proposed framework is illustrated through applications in the Chicago Metropolitan Area, with the demand estimated on the basis of existing taxi and Transportation Network Company (TNC) data.

Keywords: urban air mobility (UAM); facility location; vertiport location; infrastructure accessibility; demand coverage; agglomerative hierarchical clustering; genetic algorithm

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1. Introduction

Advanced Air Mobility (AAM) refers to the use of non-electric and electric Vertical and Short Takeoff and Landing aircraft (VTOLs/eVTOLs and STOLs), for both intra-city and inter-city transportation. Urban air mobility (UAM) is a key component of the broader AAM vision, specifically focused on integrating aerial transportation systems within urban environments. In planning for future deployment, the UAM infrastructure location problem aims to identify strategic locations for infrastructure that can accommodate take-off, landing, refueling/recharging, and parking operations, also known as vertiports/skyports. These are envisioned to be the primary terrestrial infrastructure for AAM and UAM operations, serving as departure and arrival points, and facilitating all the necessary aircraft operations [1].

The efficient deployment of vertiports is critical to the successful implementation of AAM and UAM systems. This involves strategically placing vertiports to optimize travel cost savings and ensure adequate spatial and temporal access. Objectives such as minimizing travel time, integration with existing transportation networks, and maximizing accessibility and demand coverage have been considered. Relating to the broader family of facility location problems (FLPs), this paper introduces an optimization framework for vertiport location identification. The goal of this framework is to determine the optimal locations and number of vertiport locations for a specific area, with respect to accessibility and demand coverage, under operational (capacity) and cost (budget) constraints.

Two different vertiport placement problems were formulated, one without capacity constraints, and one accounting for capacity, i.e., accounting for an upper bound regarding demand requests that a facility can serve. These are the Uncapacitated Vertiport Location Problem (UVLP), and the Capacitated Vertiport Location Problem (CVLP). These problems are variations of the traditional Uncapacitated Facility Location Problem (UFLP), and the Capacitated Facility Location Problem (CFLP), respectively.

The proposed framework solves these problems in two key steps. First, an Agglomerative Hierarchical Clustering (AHC) model is used to identify candidate vertiport locations, which serve as potential facility sites. This is done based on an estimated UAM demand profile for the service area. Additionally, a k-means algorithm was formulated to evaluate and assess the AHC model. For the second step, a genetic algorithm (GA) was developed, to identify the optimal number and locations of vertiports from the previously defined candidate set. The GA serves as the solution method for the UVLP and CVLP.

Additionally, to evaluate the proposed framework with respect to accessibility and demand coverage, different FLPs from the literature were considered, namely the *p*-center problem, the Least Service Coverage Problem (LSCP), the Maximum Coverage Location Problem (MCLP), and the *p*-median problem. The *p*-center problem corresponds to the location of p identical facilities that minimize the maximum distance between demand points and their closest-in-proximity facilities. This problem was solved with an adapted heuristic approach. The LSCP provides the minimum number of facilities located such that every demand area is covered within a predefined maximal service catchment area, measured either in time or distance units. The MCLP has as its objective the maximization of the demand covered within a maximal service distance or time window by locating a fixed number of facilities. The *p*-median problem relates to the UFLP, without budget constraints, but with an upper bound on the number of facilities that can be used. These last three problems were solved exactly with the use of linear and integer programming.

The proposed framework is applied to the Chicago area. The estimated demand profile is derived from the Transportation Network Company (TNC), and taxi trip data.

The main research questions addressed in this paper are the following:

- What are the requisite infrastructure requirements to adequately support and meet a potential volume of UAM trips?
- How can demand coverage and acceptable spatial and temporal access be incorporated into a UAM infrastructure allocation plan?
- How to identify a compromise solution between the number of vertiports, sufficient coverage, and accessibility?
- What are the trade-offs between the considered objectives?

The paper is structured as follows: First, a review of the existing literature related to various elements of the methodological framework is presented. Next, the mathematical formulations of the problems addressed by the proposed framework (the UVLP and CVLP) are introduced. This is followed by a detailed description of the methodological framework. That includes the AHC and k-means clustering models used to identify the initial set of candidate locations, and the solution method of the UVLP and CVLP, the formulated GA. Following this, the evaluation framework of the proposed framework is presented. That includes the problem formulations and solution algorithms of the FLPs considered. Next, the UAM demand profile identification process is described. The methodology is then applied to the Chicago Metropolitan Area, and the results are discussed. Finally, the concluding section summarizes the paper's contributions, outlines its limitations, and suggests directions for future research.

2. Background Review

2.1. Previous Work on the Vertiport Location Identification Problem

The identification of facility locations and infrastructure requirements for AAM and UAM operations has been studied by several research groups. Clustering methods have been widely used in vertiport location problems, with this current work using clustering

algorithms as well. The aim is to group data points in areas with concentrated demand or spatial coherence where the establishment of vertiports can effectively serve the transportation needs of a given population. The k-means clustering algorithm [2] is widely used in these studies, for identifying either candidates or final vertiport locations [3–12]. k-means clustering is typically influenced by initialization and necessitates a predetermined number of clusters [13]. Typically, the number of clusters is not known beforehand, and in such instances, validity indexes come into play to identify a suitable cluster number [14].

Syed et al. [4] concluded that the location of vertiports is more critical than their total number, which aligns with one of the research questions introduced in this current work. Holden et al. [3] used a k-means algorithm to establish a subset of origin and destination (O-D) pairs, for network optimization, using proprietary data from Uber. Sinha and Rajendran [15] developed a machine learning clustering approach for the vertiport location problem.

This current work is similar in multiple ways to Wei et al. [7], where a k-means algorithm was used to identify candidate vertiport locations and solved the uncapacitated and capacitated *p*-median problem formulations. Their method considered the cases of facility placement in both discrete and continuous spaces. Also, Venkatesh et al. [16] considered both the uncapacitated and the capacitated vertiport siting problems and used a mixed-integer programming (MIP) approach for their solution. Rajendran and Zack [6] estimated the demand for air taxi services by analyzing a subset of taxi data, and introduced a constrained clustering approach, to pinpoint potential locations for vertiport placement based on that estimated demand. A study by Sells et al. [17] used the *p*-median framework to generate and evaluate multiple facility location networks, assessing their practicality and potential for UAM-preferred trips.

GA approaches for vertiport location have also been considered by He et al. [18] and Brulin and Olhofer [19], with the latter proposing a GA solution approach to solve a bi-level network design problem with objectives of demand satisfaction and network size (upper level) and activity-based network simulation at the lower level.

Optimization formulations have also been considered, with the objectives of maximizing the ridership, revenue, and capacity of vertiports [20]. A multi-objective optimization approach was developed for a cargo and passenger aircraft service infrastructure location problem [21], with the objectives of maximizing parcel and passenger demand coverage and minimizing service distance for both parcel and passenger aircraft. German et al. [22] employed a covering facility location model to enhance the arrangement of vertiports designed for cargo delivery within the California Bay Area. An optimization model was designed by Rahman et al. [23] to pinpoint optimal vertiport locations with an objective of minimizing network distances to bus stops within each considered district.

Related to the *p*-median problem, a single-allocation p-hub median placement approach was developed in several works [24–26], with their formulations having the objectives of maximizing air taxi ridership and service revenue. Other approaches have also been used, such as a suitability analysis theory [27], location-queuing models [28], mathematical programs with bilinear equilibrium constraints [29], heuristics [30], weighted combination methods [31,32], a location-agnostic method using vacant land parcels [33], location-allocation and constrained hub allocation approaches aiming to maximize demand coverage, revenue, and travel time savings and minimize travel costs [25,34], network design approaches [35,36], and a spatial analysis method for repurposing existing infrastructure locations for UAM operations [37].

2.2. Vertiports and AAM Operations Integration Within Existing Urban Infrastructure

This section examines proposed strategies for integrating vertiports into existing infrastructure and regulatory and environmental concerns, along with ways to integrate AAM and UAM operations into existing aviation networks, based on the existing literature.

2.2.1. AAM and UAM Infrastructure Integration and Repurposing

The integration of vertiport locations with existing urban infrastructure is an important consideration in the development and implementation of AAM and UAM, especially within densely populated areas. In this context, it is essential to examine how the identified vertiport sites align with and contribute to the overall urban landscape. Mavraj et al. [38] noted that most of the AAM/UAM literature has predominantly centered on conceptual discussions or simulation-based approaches, with the exploration of vertiport networks emerging as a focal point. A critical aspect is ensuring accessibility and connectivity, by evaluating how well the vertiports integrate with existing road networks, public transit systems, and pedestrian pathways. Rahman et al. [23] formulated a methodology for pinpointing optimal vertiport locations that enhance UAM accessibility by maximizing proximity to a sizable number of bus stops while minimizing travel time. Rothfeld et al. [39] emphasized that the integration of vertiports should not solely rely on transportation time or costs; instead, there should be a focus on factors such as accessibility, environmental impact, and societal costs. Land use compatibility is also paramount, addressing how the proposed vertiports harmonize with surrounding built environments, considering zoning regulations, land use policies, and potential impacts on nearby areas.

Additionally, adapting existing facilities such as parking structures, rooftops, helipads, and underutilized transportation hubs to serve as vertiport locations could potentially reduce costs and accelerate deployment timelines [37,40,41]. By utilizing infrastructure already embedded in urban environments, stakeholders can address spatial constraints and navigate regulatory or zoning challenges associated with new construction. Yedavalli and Cohen [11] noted that UAM could initially utilize existing helipads, but the sector's growth will necessitate new facilities to accommodate aircraft operations and passenger services. However, developers of these facilities may encounter challenges, including local opposition, high infrastructure costs, and the need for seamless multimodal integration. Also, existing spatial constraints can substantially restrict the range of viable locations of such facilities [40]. Optimal vertiport location identification methods accounting for existing infrastructure, including airports and heliports, have also been proposed [17,37,42]. Factors such as potential demand, income levels, and time savings were incorporated to design an optimal vertiport network to maximize the potential UAM demand capture. Comparisons of operational costs for both existing and new infrastructure locations were conducted by Maheshwari et al. [43], who also considered operational limitations, from both the individual traveler and community perspectives.

2.2.2. Environmental and Societal Impacts

Environmental impact assessments delve into mitigating noise, emissions, and potential disruptions to the urban ecosystem, emphasizing sustainability and minimizing adverse effects on existing infrastructure. Regarding noise pollution, eVTOLs are envisioned to be quieter than helicopters, with noise reductions of approximately 10 dB when carrying similar payloads at 250 ft. However, this reduction may not suffice for public acceptance [44]. Simulations from a study in New York City show significant noise exposure: 32 operations per hour result in over 60 dB across Manhattan, while 128 operations increase levels to 65–70 dB, exceeding FAA targets but remaining within regulations [45]. Noise during vertiport departures and arrivals poses a key challenge for vertiport placement [40,46]. Kim [47] presents in detail the difference between eVTOLs and currently operational fixed-wing aircraft, as well as the fluctuations in noise during take-off, flight, and landing. The importance of noise pollution is emphasized by Kalakou et al. [48], as being one of the most significant barriers to AAM adoption.

Compliance with aviation regulations and local safety standards and coordination with relevant authorities are crucial, ensuring that proposed vertiport locations adhere to established guidelines. Additionally, community engagement plays a vital role, considering the concerns and preferences of residents and businesses to foster social acceptance and a harmonious coexistence with the existing urban community.

2.2.3. Aviation Networks, AAM/UAM Aircraft Inclusion, and Regulatory Frameworks

In terms of airspace networks within which future UAM aircraft will potentially operate, various airspace structures have been suggested by Sunil et al. [49], Pradeep and Wei [50], and Balakrishnan et al. [51], with distinct characteristics and emphasis points, in terms of airspace segmentation and aircraft routing. Such airspace structures and networks were grouped and analyzed by Mahmassani et al. [52]. The FAA [53], in their UAM Concepts of Operations, explains how the segmentation of airspace could evolve over time, and how the different airspace structures could adapt to the increasing demand for AAM and UAM services. Corridor-based networks are the preferred solution, which are envisioned to establish direct connections between vertiports, forming a network that enables point-to-point travel. The above point to the potential impacts that network choices can have in AAM and UAM operations, something that Cummings and Mahmassani [54,55] have pointed out, along with the importance of accounting for increased air traffic and the congestion that stems from it and the characteristics of the airspace structure that will be chosen. Regarding the matter of operational altitudes of AAM aircraft, according to the FAA [56], altitudes up to 4000 ft above ground level, predominantly in or around Class B and C airspace, are envisioned to be utilized, which necessitates adherence to specific regulations and equipment requirements.

Considering drones/UAVs and the regulatory framework around them, the FAA has released a set of regulations for the general use of UAVs [57]. Additionally, in collaboration with the U.S. Department of Transportation, the FAA released a framework that outlines proposed operations within Class G airspace below 400 feet above ground level, establishing key principles and ensuring equitable access to airspace for all participants [58]. At the state level, various states have enacted legislation regarding UAVs (a summary of the various state-level legislations can be found in [52]).

For feasible and efficient AAM and UAM operations, developing prediction and management models and congestion strategies is essential [59,60]. Bauranov and Rakas found that airspace structure choice is directly correlated with the level of safety, efficiency, and airspace capacity, parameters influencing demand and operations optimization [61], something which Ale-Ahmad and Mahmassani [62,63] and Mahmassani and Ale-Ahmad [64] worked on, focusing on a potential urban air taxi service.

2.3. Ground Transportation Infrastructure Location Identification Literature

This work also has similarities with various ground transportation infrastructure location problems. Determining stations/stops/docking location placement has been studied widely, for different transportation modes. For the bus stop location problem, GIS-based and optimization methods, as well as Voronoi diagram-based approaches, have been used [65–68]. In the rail sector, the identification of feasible urban rail station locations [69,70], along with high-speed rail station placement, has been performed [71–74], based on genetic, GIS-based, and mixed-integer algorithms, as well as passenger travel cost savings maximization- and travel time minimization-based models. For the bike-sharing docking sites identification optimization problem, mixed-integer programming, location-allocation models, coverage maximization, demand prediction-based, and Artificial Neural Network prediction formulations have been used [75–79]. For the electric vehicle charging station allocation problem, mixed-integer, along with location-allocation and minimization of access cost, formulations have been proposed [80–82].

2.4. Genetic Algorithm Introduction

Genetic algorithms follow several principles originating from the biological evolution process [83]. A GA has components such as chromosome representation, fitness selection, and biologically inspired operators (corresponding to selection, mutation, and crossover processes), inspired by the principles of natural selection and genetics, and was introduced by Holland [84,85], and named the Simple Genetic Algorithm (SGA) [86]. Typically, chromosomes adopt a binary string format, with each distinct location on the chromosome

having values of 0 and 1. Chromosomes are treated as points in the solution space and undergo iterative processing using genetic operators, ultimately updating the population. The fitness function evaluates all chromosomes in the population [87]. In the selection process, chromosomes are chosen based on their fitness values for further processing. The crossover operator involves randomly selecting a specific location of the chromosome and altering subsequences between chromosomes to generate offspring. In mutation, some chromosome bits are randomly flipped based on probability.

2.5. Facility Location Problem Approaches

The facility location problem (FLP) family constitutes a class of optimization problems essential in logistics, operations research, and supply chain management. Location problems and the theory and models behind them were introduced by Larson and Odoni [88] and Daskin [89]; they identified four major modeling segments of this family of problems: analytic models, continuous location models, network models, and discrete location models. An early analytical optimization formulation of the plant location problem (i.e., the FLP) was implemented by Balinski [90]. At its core, the FLP involves determining optimal locations for facilities, such as emergency centers [91], warehouses [92], factories, or service centers, with the objective of minimizing overall costs or maximizing efficiency. This family encompasses various specific problem formulations, such as the single-FLP and multi-FLP, covering, center, and median location problems [93], the UFLP [94] and CFLP [95], stochastic location problems [96], and the multi-criteria FLP [97,98].

The latter research team integrated the goals of three well-defined problems, the *p*-median problem, the MCLP, and the *p*-center problem, with an objective of discovering a collection of Pareto-optimal solutions and a unified compromise solution for all three objectives. Related to this approach, the current work considered all these problem formulations, along with the LSCP, but not to find a unified solution for each problem's objective, but rather to compare each one as a different approach to and objective for the vertiport location identification problem.

2.5.1. Uncapacitated Facility Location Problem

The Uncapacitated Facility Location Problem is a classic optimization problem, which involves determining the optimal locations for facilities to be opened and assigning customers to these facilities in a way that minimizes the total cost [94,99]. The objective is to balance the fixed costs associated with opening facilities and the variable costs related to serving customers. In this problem, facilities have unlimited capacity, meaning they can serve an unlimited number of customers without constraints. The goal is to strategically position the facilities to minimize the overall cost of establishing and operating them while efficiently meeting the demand from customers [100,101].

Exact algorithms have been also used for the solution of UFLP formulations, including branch and bound approaches [102,103], linear programming [104], branch and cut [105,106], and projection methods [107]. Approximation algorithms have also been used for this specific problem [108–111]. Heuristics such as multi-start and neighborhood search approaches [112,113], as well as metaheuristics, e.g., tabu search [114–116], ant colony optimization [117], evolutionary algorithms [118,119], simulated annealing [120], and particle swarm algorithms [121] have also been used for the UFLP [122].

Genetic Algorithm Approaches for the UFLP

Genetic algorithms have proven to be effective in addressing the UFLP [123–127]. A variant of the UFLP is the Uncapacitated Single Allocation Hub Location Problem, for which GAs have also been used as well [128–130]. Potential facility locations and customer assignments are represented as chromosomes, where each gene corresponds to a facility or customer. The population undergoes evolutionary processes such as crossover and mutation to generate new solutions iteratively. The evaluation of these solutions involves calculating the total cost, considering fixed setup costs and variable transportation costs.

Genetic algorithms excel in exploring the vast solution space of the UFLP, providing a flexible and adaptive approach to finding near-optimal solutions.

2.5.2. Capacitated Facility Location Problem

The Capacitated Facility Location Problem has as an objective to determine the optimal locations for opening facilities and method of assigning customers to these facilities in a way that minimizes the total cost, considering both fixed facility setup costs and variable costs associated with serving customers. Importantly, the facilities in the problem have limited capacities, introducing a capacity constraint that restricts the number of customers each facility can serve. Variants of the formulation exist as well, with an example being the CFLP with mobile facility locations [131].

Exact algorithmic formulations have been popular for this problem, such as mixed-integer [132–134] and linear programming [135], along with solution approaches such as branch and bound [136–138], Lagrangian relaxation [139–147], branch and cut and price [148,149], and cross decomposition methods [150], among others.

Approximation algorithms [151,152], and especially heuristic algorithms [153–159], greedy heuristics [160,161] along with metaheuristics [162], such as tabu search [163–165] and search algorithms [166], have also been used for such problems.

Genetic Algorithm Approaches for the CFLP

Similar to the UFLP, GAs have been used in the literature for CFLPs, with the basic principles remaining similar. However, the handling of capacity constraints introduces a layer of complexity, requiring tailored genetic operators to efficiently explore the solution space. Additionally, not all the demand requests can be assured to be satisfied, such as in the partial demand satisfaction formulation by Nasiri et al. [167], with other GA approaches also being implemented [168–172], based on different genetic operations.

2.5.3. Location Set Covering Problem

The Location Set Covering Problem is a combinatorial optimization problem commonly encountered in facility location analysis. The objective of the LSCP is to determine the optimal locations for a predefined set of facilities to efficiently cover a set of demand points or regions. Each potential facility has associated coverage, and the goal is to minimize the total number of facilities needed to cover all demand points, considering coverage constraints. Such problems find applications in various fields where the efficient placement of facilities is crucial to maximizing coverage and minimizing costs, such as emergency services planning, e.g., emergency facility locations [173], emergency vehicle siting [174,175], fire station allocation [176], queueing theory models for location problems [177,178], location problems with varying demand over time and facilities with dynamic locations [179], and other applications.

Mathematically, the LSCP is formulated as a linear programming (LP) problem with a single cut constraint, with Toregas et al. [173] noting that in addition to LP, cutting plane techniques, reduction techniques [179], and implicit enumeration are mostly used in such problems. Additionally, the use of heuristics [180], such as search algorithms for the solution of the Lagrangian approximation of the problem [181], metaheuristics [182], and integer programming [183,184], among other techniques, have also been used.

2.5.4. Maximal Coverage Location Problem

The primary objective of the Maximal Coverage Location Problem is typically to identify the optimal locations of a given set of facilities that, when activated, collectively cover as much of the target region as possible [185]. The coverage is often defined in terms of a specified distance or other relevant criteria. The MLCP is inherently a trade-off between the number of facilities to be opened and their strategic locations, aiming to balance operational efficiency and cost-effectiveness while meeting coverage requirements. It has been used for various planning purposes, such as emergency vehicle siting [186–188], warehouses,

control facilities [189], service centers [190], emergency response units [191], fire prevention facilities [192,193], and electric vehicle (EV) charging stations [194], to maximize the coverage of a given geographic area, with many other potential areas of application [195]. Several methods have been used, with different heuristics [196–199] and metaheuristics [200] being one of the main categories, along with approximation algorithms [201], and Lagrangian relaxation [202–204]. Exact algorithmic methods associated with linear [205], integer [206], and mixed-integer [207] programming formulations have also been used.

2.5.5. *p*-Median Problem

The *p*-median problem [208,209] involves selecting *p* facilities from a set of potential locations to minimize the overall cost or distance between each demand point and its nearest facility. The term "*p*" refers to the predetermined number of facilities to be chosen, often influenced by factors such as budget constraints or capacity limitations. The objective is to strategically position these *p* facilities to efficiently serve a given set of demand points, optimizing resource allocation and minimizing the total cost of service provision. By adjusting the objective function of the *p*-median problem, several special cases and similar facility location problems can be derived [210,211]. The *p*-median problem diverges from the facility location problem in two main aspects: firstly, there is no associated cost for initiating facilities, and secondly, there exists an upper limit on the number of facilities that can be initiated. It finds applications in a diverse range of fields, including healthcare facility placement [212], fire station siting [213], EV charging station placement [214,215], and public service facilities in general [216]. Methods like the previously introduced problems, such as heuristics [217–224], and specific heuristic groups such as tabu search [210], simulated annealing [225], GAs [226–230], greedy heuristics [231,232], and Lagrangian relaxation [233–236], have been used. Additionally, mixed-integer programming [237], linear programming approximation [238] and relaxation [239], and column-and-constraint generation algorithms [240] are among the approaches that can be found in the literature.

2.5.6. *p*-Center Problem

The *p*-center problem considers the identification of a limited number of facilities within a given geographical region to efficiently serve the demands of customers or clients [208,209,241]. The primary objective is to locate facilities that minimize a maximum loss [241], or to minimize the maximum distance between a customer and its assigned facility, emphasizing in that way the optimal accessibility that can be offered by the service, defined as an integer programming (IP) problem. Unlike some facility location problems, this problem is characterized by the absence of setup costs associated with opening facilities, and it introduces an additional constraint by limiting the total number of facilities to be opened. Approximation algorithms [242], such as greedy algorithms [243,244], local search algorithms [245], robust optimization [246], linear reformulation, Bender's dual cutting plane, the column-and-constraint generation method, and integer programming [247], have been used for this problem.

3. Materials and Methods

Initial candidate vertiport locations are identified via an AHC model, by assigning data points corresponding to UAM demand requests to different clusters. Additionally, a k-means algorithm is used for the same purpose, to compare and create a benchmark for the AHC model's solution. The estimation of UAM demand was implemented using TNC and taxi trip data, where travel time and distance thresholds are utilized as determinants for demand identification.

Based on the candidate locations identified, the GA can be deployed for the solution of the UFLP and CFLP. In the following, we describe how different FLP formulations were considered and solved exactly with linear and integer programming, to compare the results of the GA, focusing on the aspects of demand coverage and accessibility. These

formulations are the MCLP, LSCP, p-median, and p-center formulations. Table 1 summarizes the mathematical notation used.

Table 1. Summary of mathematical notation and parameter values.

Math. Representation	Notation Explanation
q_{acc}^{ov}	Access travel cost to vertiport v via walk/vehicle, from origin o_r, trip r
$t_{r_{acc}}^{ov}$	Access travel time to vertiport v via walk/vehicle, from origin o_r
q_{egr}^{vd}	Egress cost from vertiport v via walk/vehicle, to destination d_r
t_{egr}^{vd}	Egress travel time from vertiport v via walk/vehicle, to destination d_r
gq_{UAM}^{r}	Generalized cost of UAM trip for request r
q_{UAM}^{ij}	Travel cost of UAM trip between vertiport i and vertiport j
ft_{UAM}^{ij}	Average cruise UAM flight travel time, trip r, vertiport i and j
v_{UAM}	Average aircraft speed (196 km/h, from [248,249])
$tt_{UAM_{sp}}^{r}$	Cruise UAM flight travel time for request r, based on v_{UAM} and SLoC
γ_{α}	UAM travel time reduction factor, based on [250,251]
tt_{UAM}^{r}	Cruise UAM flight travel time for request r, based on γ_{α}
$q_{ground}^{od_r}$	Travel cost for completing OD trip r via ground transportation
$tt_{ground}^{od_r}$	Total travel time for completing OD trip r via ground transportation
VOT, ρ_w	Value of time, 16.5$\frac{\$}{h}$, [252,253], walk penalty factor, $\rho_w = 2$, [254]
tot_{cs}	Total cost savings from opting for UAM instead of ground transportation
cs_i	Generalized cost per vertiport, based on [52,251,255], $cap_c^v = \$1,550,000$
$t_{b_{aw}}$	Time for boarding, alighting, take-off and landing, 10 min [255]
lat_o^r, $long_o^r$, lat_d^r, $long_d^r$	Latitude and longitude of origin and destination vertiports, trip r
x_v, b_{tot}	Number of needed vertiports, available budget (upper bound)
cpm_{air}, c_{base}	UAM cost per mile, 4.73$\frac{\$}{\text{mile}}$ [1,5], UAM base cost, USD 15/trip [256]
$cpm_{ground_{TNC_{taxi}}}$	TNC/taxi cost per mile, 5.15$\frac{\$}{\text{mile}}$, based on [257–259]
cpm_{ground}	Personal vehicle cost per mile, 0.78$\frac{\$}{\text{mile}}$, [260]
t_{UAM}^{w}, t_{UAM}^{e}	Vertiport wait time (5 min), board and alight time (5 min)
$c_{parking}$, R	Parking cost, 5.2$\frac{\$}{h}$, [261,262], Earth's radius (3959 miles)
a_r^{ij}	$= \begin{cases} 1, \text{ if trip request } r \text{ satisfied via UAM service} \\ 0, \text{ otherwise} \end{cases}$
g_r	$= \begin{cases} 1, \text{ if trip request } r \text{ satisfied via ground transport} \\ 0, \text{ otherwise} \end{cases}$
f_r^a	$= \begin{cases} 1, \text{ if origin vertiport of } r \text{ not activity origin} \\ 0, \text{ otherwise} \end{cases}$
f_r^e	$= \begin{cases} 1, \text{ if destination vertiport of } r \text{ not activity destination} \\ 0, \text{ otherwise} \end{cases}$
mf_r^a	$= \begin{cases} 1, \text{ if ground transport for access is car(personal,} \\ \text{TNC/taxi)} \\ 0, \text{ if it is walk} \end{cases}$
mf_r^e	$= \begin{cases} 1, \text{ if ground transport for egress is car}\left(\frac{TNC}{taxi}\right) \\ 0, \text{ if it is walk} \end{cases}$
a_r^{ij}	$= \begin{cases} 1, \text{ if segment of trip request } r \text{ visits vertiports } i \text{ and } j \\ 0, \text{ otherwise} \end{cases}$

Table 1. *Cont.*

Math. Representation	Notation Explanation
$a_r^{ij}, g_r, f_r^a, f_r^e, mf_r^a, mf_r^e, \psi_i, \varphi_i$	Binary decision variables
tc_{ij}, s_a^i	Cost for facility i serving demand node j, demand nodes served by i
m_{ij}	Fraction of customer zone $j's$ demand satisfied by facility i
x_{ij}	Distance or time metric between node i and node j
w_d	Acceptable walking distance or travel time upper bound
φ_i	$= \begin{cases} 1, \ if \ one \ or \ more \ facilities \ i, \ i \in I, \ have \ \ x_{\ i \in Ij} \leq w_d \\ 0, \ otherwise \end{cases}$
$e_d^i\left(X_j\right), \ p$	Euclidean distance, number of predefined facilities
$\psi_i, \ \zeta_{ij}$	$= \begin{cases} 1, \ if \ facility \ i \ is \ open \\ 0, \ otherwise \end{cases}, \begin{cases} 1, \ if \ facility \ i \ serves \ demand \ request \ j \\ 0, \ otherwise \end{cases}$

3.1. Proposed Vertiport Location Identification Framework

This section describes the problems considered, their formulations, and the corresponding solution methods.

3.1.1. Problem Formulations

The first set of FLPs considered are the UVLP and the CVLP, adapted formulations of the traditional UFLP and CFLP, respectively. The following assumptions are made about the network: only one facility can be placed at a certain location, and a customer-to-server system is considered where the demands travel to the facilities for service.

Mathematical Formulation of the UVLP

A set of facilities, p, aim to serve a set of demand requests, k, where $j \in j_z$, meaning that each request j of the set k corresponds to a demand zone $j_z \in K_z$. Each facility i has a fixed capital opening cost cs_i, and a cost tc_{ij} to serve demand request j, with m_{ij_z} being the fraction of customer zone $j_z's$ demand satisfied by facility i. The objective is the minimization of the total cost, while also minimizing the average travel time of demand requests from their closer facility, trying to find the optimal number of facilities that satisfies Equation (1).

$$min \sum_{i=1}^{p} \sum_{j=1}^{k} \left(tc_{ij} \cdot m_{ij_z} \cdot \zeta_{ij} + t_{j_{acc}^{ov}} \cdot \zeta_{ij} \right) + \sum_{i=1}^{p} cs_i \cdot \psi_i \tag{1}$$

is subject to

$$\sum_{j_z=1}^{K_z} \sum_{i=p}^{p} m_{ij_z} = 1, \ i = 1, 2, \ldots, p \tag{2}$$

Equation (2) corresponds to the fact that the summation for all facilities i, for all fractions that correspond to customer zone j_z, need to sum to one. In addition, Equation (3) ensures that a demand request j can be served from facility i, only if its distance π_{ij} from facility i is within the designated service radius upper bound, d_u. $I\left(\pi_{ij} \leq d_u\right)$ is an indicator function that is equal to one if $\pi_{ij} \leq d_u$, and zero otherwise.

$$\zeta_{ij} \leq \psi_i I\left(\pi_{ij} \leq d_u\right) \tag{3}$$

Equation (17) ensures that all demand requests will be served by an available facility, and $\psi_i, \zeta_{ij} \in \{0, 1\}$. Equation (4) represents the budget constraint considered.

$$\sum\nolimits_{v \in V} n_p * cap_c^v \leq b_{tot} \tag{4}$$

Equation (5) ensures that a facility will not be opened unless it can serve (distance-wise) a certain fraction (based on a lower bound) of the total demand that could come from different customer zones $j_z \in K_z$, where td is the total demand, and $1 + \frac{\sum_{j_z}^{K_z} m_{ij_z}}{td}$ is a service standard that each facility needs to have, where $\lceil \cdot \rceil$ corresponds to a ceiling function.

$$\psi_i \leq \left\lceil \left(1 + \frac{\sum_{j_z}^{K_z} m_{ij_z}}{td} \right) \sum_{j \in k} \zeta_{ij} \right\rceil \tag{5}$$

Mathematical Formulation of the CVLP

The formulation of the CVLP is analogous to the one for the UVLP, with the main difference of a capacity constraint. Equation (6) reflects the minimization of the total cost, where $\psi_i, \zeta_{ij} \in \{0, 1\}$.

$$min \sum_{i=1}^{p} \sum_{j=1}^{k} \left(tc_{ij} \cdot m_{ij_z} \cdot \zeta_{ij} + t_{j_{acc}}^{ov} \cdot \zeta_{ij} \right) + \sum_{i=1}^{p} cs_i \cdot \psi_i \tag{6}$$

is subject to Equation (2), and

$$\sum_{j=1}^{k} m_{ij_z} \leq cap_i, \; i = 1, \ldots, p \tag{7}$$

The addition of the capacity constraint (Equation (7)) differentiates this formulation from the UVLP. The hourly capacity (which is equivalent to operations being satisfied per hour) of each vertiport was thirty-two flights (either inbound or outbound), to use a pessimistic threshold, and one that could correspond to initial years of operation of a new transportation mode. Since there is no limitation on the overall capacity, the total capacity can be sufficient or insufficient to cover all the demands. Table 2 summarizes the data used.

Table 2. Urban Air Mobility operations volume.

Hourly Operations Per Vertiport	Aircraft Type	Data Used	Source
53	VTOL/eVTOL	Estimated	[3]
45	VTOL/eVTOL	Estimated	[4]
50	VTOL/eVTOL	Estimated	[263]
1250	VTOL/eVTOL	Estimated	[264]
298	Helicopter	Existing	[265]
600	Helicopter	Existing	[266]

In line with the UVLP formulation, Equation (8) represents the budget constraint, Equation (9) ensures that a demand request will only be served from a facility if that request is within the service radius of that facility, and Equation (10) ensures that a facility will only be opened if it can serve at least a certain demand percentage.

$$\sum_{v \in V} n_p * cap_c^v \leq b_{tot} \tag{8}$$

$$\zeta_{ij} \leq \psi_i I\left(\pi_{ij} \leq d_u \right) \tag{9}$$

$$\psi_i \leq \left\lceil \left(1 + \frac{\sum_{j_z}^{K_z} m_{ij_z}}{td} \right) \sum_{j \in k} \zeta_{ij} \right\rceil \tag{10}$$

3.1.2. Methodological Framework

The approach taken for the solution of the UVLP and CVLP consists of the identification of candidate vertiport locations (via an AHC model), which are then provided to the solution method, i.e., the developed GA.

Candidate Locations Identification—Agglomerative Hierarchical Clustering

Agglomerative clustering is a hierarchical clustering algorithm, which considers each data point as an individual cluster and then iteratively merges the closest clusters until only one cluster remains, forming a hierarchical tree or dendrogram [267]. AHC divides the dataset into individual nodes, and then iteratively combines the most proximate pair of nodes into a new node. This process continues until only one node remains, encompassing the entire dataset [268]. The method's essence lies in its bottom-up approach, where proximity between clusters is determined based on a specified distance metric, such as Euclidean distance or other dissimilarity measures. Agglomerative clustering can be characterized as greedy in the algorithmic sense, employing a sequence of steps to construct the desired data structure [269]. The algorithm implemented in this work uses libraries from Python [270], which utilize the Ward hierarchical clustering method [271]. This is a greedy algorithm, following a bottom-up approach, commencing with singleton clusters [272]. This method is based on a sum-of-squares criterion, and at each step it selects, in a greedy fashion, two clusters from the existing clustering and generates classes that minimize within-class dispersion at each binary fusion [273].

Solution Method

A GA rearranges chromosomes (i.e., candidate choices) using simulated genetic processes like crossover (i.e., configuration exchange) and mutation (adjustment of candidate configurations), with Figure 1 presenting the workflow of a generalized GA and the GA introduced in this work, with the former beginning by selecting an initial population of chromosomes and evolving through successive iterations by applying crossover and mutation operators. These operations result in a new population generated at each iteration. Consequently, each cycle within the loop is referred to as a generation process [274].

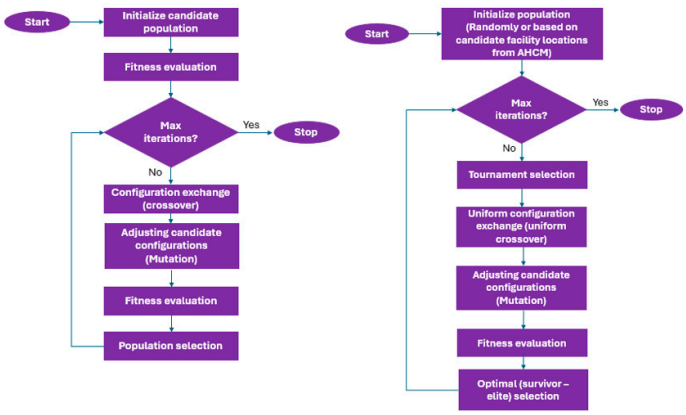


Figure 1. Genetic Algorithm flowcharts.

In the proposed GA for this work, a uniform crossover operator was used, and the element of elitism was included. The elitist technique operates with a distinct population known as the secondary population, which encompasses all or a subset of potential Pareto-optimal solutions discovered throughout the search process [275]. This set is independent of the main population and, upon the completion of the entire search, contains the set of all non-dominated solutions generated. An elitism control parameter is usually introduced to regulate the level of elitism. This parameter determines the maximum number of non-dominated solutions, referred to as the elite, which will be incorporated into the main population. Following, a brief overview of the algorithm's steps is provided:

- Initial population: Determines the population size, and it is of high significance, since it can play a decisive role in reaching an acceptable solution with a reasonable computational time [167].
- Selection: It involves both parent and survivor selection processes.
    - Parent selection in the proposed genetic algorithm employs two strategies. For the first, a percentage θ, $\theta > 0$ of parents are uniformly chosen from the top ξ percentage of the best solutions in the current generation. The remaining $100 - \theta$ are determined through a tournament selection approach [276]. First, it randomly selects a subset of individuals from the population, known as the tournament pool. The fitness of each contender in the pool is evaluated, and the individual with the highest fitness is chosen as the winner. This winner is then selected as a parent for the next generation. The process is repeated until the desired number of parents is obtained.
    - For survivor selection, the next generation is determined from the current parents and children using an elitism mechanism. This process persists until the current generation is sorted, and the population size is filled with the best solutions from the entire generation, ensuring their survival in the subsequent generation.
- Crossover: This process oversees combining the properties of two parents. Different crossover operators exist, with one-point, two-point, and uniform operators being the most common [277]. In a one-point crossover, a single crossover point is randomly selected along the length of the parents' chromosomes. A two-point crossover involves selecting two random crossover points along the length of the parents' chromosomes. The genetic material in each case is swapped between the parents. In a uniform crossover, each gene in the offspring has an equal probability of coming from either parent. A binary mask is used to determine which genes are inherited from each parent.
- Mutation: This process ensures that premature convergence will be avoided, as well as local optima. Two of the nodes are randomly selected, and their order is exchanged between them.
- Fitness evaluation: The quality of the solutions is evaluated to guide the decision-making process on whether to retain or discard them from one generation to the next. This entails preserving and transmitting characteristics that enhance the quality of a given solution. It is common for the objective function to be the fitness function.

3.2. Evaluation Approach of Proposed Methodology

To evaluate the proposed framework with respect to accessibility and demand coverage, linear and integer programming were used to solve the following FLPs that consider these objectives.

3.2.1. Problem Formulations

This subsection introduces the problem formulations of the FLPs considered to evaluate the proposed framework.

Mathematical Formulation of the LSCP

From Toregas et al. [173], the following IP problem was formulated, with an objective of minimizing the total number of facilities used (Equation (11)). An acceptable walking distance or travel time w_d to a facility for each demand point is defined, and only a set of nodes i (denoted as S_i) within w_d can offer an acceptable service to i. Also, the distance or time metric from node i to node j is denoted as x_{ij}, and, therefore, for the set of nodes S_i, we have that $S_i = \{j | x_{ij} \leq w_d\}$. Assuming n demand points/nodes exist, there will be n S_i sets, with each having (at least) one member, and since S_i is not dependent on the nature of

the nodes j, a facility location could be either a demand point node, or any other location. Following, the problem's formulation as an integer programming model is presented.

$$min \sum_{i=1}^{n} \psi_i \tag{11}$$

is subject to

$$\sum_{i=1}^{n} \psi_i \geq 1,\ i = 1, \ldots, n \tag{12}$$

$$\psi_i \in \{0, 1\},\ i = 1, \ldots, n \tag{13}$$

where Equation (12) corresponds to the service constraint for demand node i, ensuring that each demand point is served by at least one facility, and Equation (13) to the integrality constraint. According to Daskin [89], the set covering problem is an NP-complete problem, involving the selection of a minimum-cost subset of facilities from a finite set of candidates such that every demand node is served by at least one facility. The proof of the NP-complete problem case was derived by Garey and Johnson and is not included in this text because it necessitates defining several other NP-complete problems [278]. These problems have minimal direct relevance to location modeling, aside from their role in demonstrating that the set covering problem is NP-complete.

Mathematical Formulation of the MCLP

According to Church and ReVelle, the maximal covering location problem aims to maximize the population that can be accommodated within a specified service distance or time, considering a constrained number of facilities [185]. Megiddo et al. demonstrated that the maximum covering problem on a general network is NP-complete [190]. However, for tree networks, they provide a polynomial-time algorithm to solve the problem.

First, K and P are denoted as sets of demand nodes and facility sites, respectively. Analogous to the LSCP, an acceptable walking distance w_d to a facility for each demand node is defined, and only a set of nodes i (denoted as S_i) within w_d can offer an acceptable service to i. Also, the shortest distance from node i to node j is denoted as x_{ij}, and, therefore, for the set of nodes S_i, we have that $S_i = \{j | x_{ij} \leq w_d\}$, with p representing the number facilities to be created, and s_a^i the demand nodes served by node i. The objective is to maximize the number of people covered within the designated distance (Equation (14)).

$$max \sum_{i=1}^{n} s_a^i \varphi_i \tag{14}$$

is subject to

$$\sum_{j=1}^{N_i} \psi_j \geq \varphi_i,\ i \in K \tag{15}$$

Equation (15) allows for φ_i to be equal to 1 if one or more facilities are located such that they have a distance from demand node i less than or equal to the acceptable distance w_d.

$$\sum_{i=1}^{J} \psi_i = p \tag{16}$$

Equation (16) ensures that the number of facilities that will be opened is equal to the predefined number of facilities p. Equations (17) and (18) are the integrality constraints on the decision variables.

$$\psi_i \in \{0, 1\},\ i \in P \tag{17}$$

$$\varphi_i \in \{0, 1\},\ i \in K \tag{18}$$

The solution to the above problem offers the maximum number of demand requests that can be covered, along with the p facility locations that can achieve that maximum coverage. It is formulated as a linear programming problem, and based on Daskin [89], by relaxing the integrality constraints, setting upper-bound constraints of one on all the coverage variables φ_i; the resulting linear programming problem can then be solved.

Mathematical Formulation of the p-Median

Based on ReVelle and Swan, the p-median problem can be expressed via the following IP formulation, with the objective function on Equation (19) corresponding to the minimization of the demand-weighted distance between a demand point and its closest-in-proximity facility location [207].

$$min \sum_{j=1}^{k} \sum_{i=1}^{k} s_a^i x_{ij} m_{ij} \tag{19}$$

is subject to

$$\sum_{j=1}^{k} m_{ij} = 1, i = 1, \ldots, k \tag{20}$$

Equation (20) ensures that each demand point is assigned to exactly one facility.

$$m_{jj} - m_{ij} \geq 0,\ i = 1, \ldots, k, j = 1, \ldots, k, i \neq j \tag{21}$$

Equation (21) upholds the location and allocation variables connection.

$$\sum_{j=1}^{k} m_{jj} = p \tag{22}$$

Equation (22) constrains the problem to a predefined number of facilities, p. The constraints of Equation (23) are the standard integrality constraints.

$$m_{ij} \geq 0, m_{ji} \geq 0,\ i = 1, \ldots, k, j = 1, \ldots, k \tag{23}$$

Linear programming was used to solve the problem under consideration. The p-median formulation assumes that facilities are positioned on the network's nodes. However, this assumption can result in suboptimal solutions for the set covering, maximum covering, and p-center problems [89]. Nevertheless, Hakimi demonstrated that for the p-median problem, there is at least one optimal solution that involves placing p facilities on the network's nodes [208].

For a fixed p, the p-median problem can be solved in polynomial time relative to the number of nodes. However, for even moderate values of the number of nodes (N), and the number of facilities to be located (p), the number of potential solutions that need to be evaluated becomes extremely large [89]. Additionally, when p is variable, the problem remains NP-complete [278]. This is because solving all p-median problems by enumeration for p = 1 to $p = N$ requires exponential time in N, since $\sum_{q=1}^{N} \binom{N}{q} = 2^N - 1 \approx O(2^N)$. Therefore, to solve higher-sized problems than the considered problem in this work, within a reasonable time frame, heuristic algorithms could be needed.

Mathematical Formulation of the p-Center

Given a set of k demand points, each accompanied by a specific weight, the objective function (Equation (24)) aims to identify p new facilities that minimize the maximum

weighted Euclidean distance (denoted as $e_d^i(X_j)$) between each demand point and its nearest new facility [208,279].

$$\min \left\{ \underset{\substack{1 \le i \le k \\ 1 \le j \le p \\ X_1, \ldots X_p}}{max} \left\{ \omega_{ij} e_d^i(X_j) \right\} \right\} \tag{24}$$

is subject to

$$\sum_{j=1}^{p} \omega_{jj} = 1, \; i = 1, \ldots, k \tag{25}$$

where $\omega_{ij} = \begin{cases} 1, \; if \; demand \; point \; is \; assigned \; to \; facility \; j \\ 0, \; otherwise \end{cases}$, and $X_j, j = 1, 2, \ldots, p$ is the optimal location of facility j.

To solve this problem, an adapted heuristic approach based on algorithms by Kariv and Hakimi [280] and Handler and Mirchandani [281] was used, which generates and solves a series of set covering problems. The objective is to locate facility locations such that the level of service at the worst possible scenario is as good as possible. The pseudocode of the algorithm is provided below, where $K = ||\kappa_{ij}||$ is the shortest distance matrix with n rows and $|C|$ columns, C is the set of all points corresponding to local centers, with a local center existing at a point c when the minimum distance from c to an arbitrary point x is equal to the minimum distance from c to another arbitrary point y, κ_{ij} is the shortest distance from node v_i to the j^{th} candidate center, Ξ_p is an initial solution, r_p is the p-radius, and $r_p = \min_{\Xi_p} max_{(v_i \in V)} \min_{j \in \Xi_p} \kappa_{ij}$.

When the number of facilities to locate p is held constant, the p-center problem can be solved within polynomial time [89]. To illustrate this, it suffices to recognize that for a network comprising n nodes, each of the $O\binom{n}{p} = O(n^p)$ possible combinations of p locations needs to be assessed. However, the p-center problem is NP-complete for variable values of p across general graphs [278] and could lead to significantly high computational times [280].

3.2.2. Solution Methods

Linear and integer programming were used to solve the LSCP, MCLP, and p-median problem, and a heuristic method (Algorithm 1) was sued to solve the p-center problem. As solver software, Gurobi 10.0.2 in Python was used, with an academic license [282].

Algorithm 1: *p*-center Solution Algorithm

1 Choose arbitrary initial solution Ξ_p
2 Let $\alpha = \underset{v_i \in V}{\max} \underset{j \in \Xi_p}{\min} \kappa_{ij}$
3 Update matrix $\Delta = ||\delta_{ij}||$ where
4 $\quad \delta_{ij} = \begin{cases} 0, \; if \; \kappa_{ij} \ge \alpha, i = 1, 2, \ldots, n, j = 1, 2, \ldots, |C| \\ 1, \; otherwise \end{cases}$
5 Solve the covering problem
6 $\quad \rho = min \; e^r x$
7 $\quad$ subject to
8 $\quad\quad \Delta x \ge e^r$
9 $\quad\quad x_j \in \{0, 1\}, j = 1, 2, \ldots, C$
10 $\quad\quad$ where $e^r = (1, 1, \ldots, 1)$
11 ***If*** $\rho > p$
12 $\quad\quad$ Terminate, and set $r_p = \alpha$
13 ***Else***
14 $\quad\quad$ Update Ξ_p with improved solution, go to line 2

3.3. UAM Demand Identification

The clustering methods introduced use demand points for the UAM service. In the applications to Chicago described in the next section, we estimated these demand points from the TNC and taxi trip requests that met certain travel time and distance thresholds. Two options were assumed, ground transportation or a multimodal UAM service, and, if the origin and/or destination vertiports were not the activity-base origin and destination, then additional trip leg/s were generated, which could be completed via walking, personal vehicle, or TNC/taxi. Figure 2 presents the two trip options (ground in green, UAM in blue).

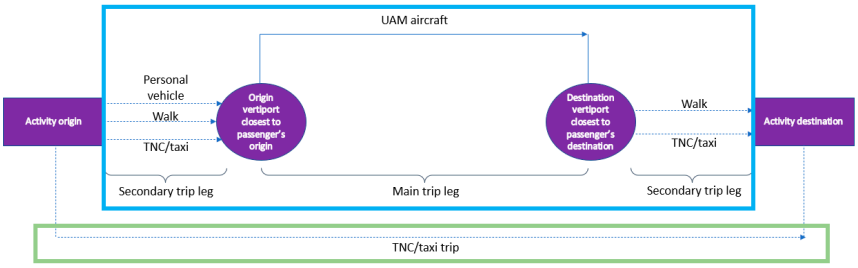


Figure 2. Multimodal Urban Air Mobility service.

Individuals will choose UAM over ground transportation for their specific origin–destination trip, in the case of the total travel and generalized travel costs of the UAM service being lower than the ones of ground transportation. Table 3 presents the pricing scheme for each available travel mode used in the Chicago application.

Table 3. Pricing schemes for available modes.

Main Trip Leg	
Transportation Mode	**Pricing Strategy**
UAM service	$c_{base} + c_{e_{legs}} + cpm_{air} * (distance\ travelled)$
Ground transportation (TNC/taxi)	$cpm_{ground_{TNC_{taxi}}} * (distance\ travelled)$
Secondary Trip Leg/s $\left(c_{e_{legs}}\right)$	
Transportation Mode	**Pricing Strategy**
Ground transportation (TNC/taxi)	$cpm_{ground_{TNC_{taxi}}} * (distance\ travelled)$
Ground transportation (personal vehicle)	$cpm_{ground} * (distance\ travelled) + c_{parking}$
Walk	$(walk\ travel\ time) * \rho_w * VOT$

From the Spherical Law of Cosines (SLoC), the distance between origin and destination vertiports and, consequently, the cruise travel time can be found (Equation (31)). UAM cruise travel time (Equation (32)) was assumed to be an average value of Equations (30) and (31). Decision variable a_r^{ij} specifies if a trip request r was satisfied via UAM, where $o_r \neq d_r$, and $i \neq j$. Equations (26) and (27) denote cost and travel time calculation formulas for the UAM service:

$$gq_{UAM}^r = \sum_i \sum_{j \neq i} q_{UAM}^{ij} * a_r^{ij} + \sum_{o_r} q_{acc}^{ov} * f_r^a * mf_r^a + \sum_{d_r} q_{egr}^{vd} * f_r^e * mf_r^e \quad (26)$$

where $o_r \in O$ is the set of origins, and $d_r \in D$ is the set of destinations of each trip request r, and $i, j \in V$, $i, j = \{1, \ldots, n_v\}$ for a set of vertiports V, with $V \subseteq N$. A set of nodes N, $l \in N$, corresponding to each cluster that was identified by the AHC algorithm, can be considered as potential demand centers providing service to customers that want to use the air-ride-sharing service, i.e., potential vertiport locations. And, consequently, V is a

subset of N since there is a possibility that not every candidate node will eventually be a vertiport location.

$$tt^{r}_{UAM} = \sum_{i} \sum_{j \neq i} ft^{ij}_{UAM} + t^{e}_{UAM} + t^{w}_{UAM} + \sum_{o_r} t^{ov}_{r_{acc}} * f^{a}_{r} + \sum_{d_r} t^{vd}_{egr} * f^{e}_{r} \quad (27)$$

For the choice between ground and UAM transportation, the major criterion considered consists of the cost savings by opting to use UAM instead. This index accrues from Equation (28).

$$tot_{cs} = gq^{r}_{UAM} - q^{od_r}_{ground} \quad (28)$$

Therefore, it is assumed that for UAM to be chosen, Equation (29) needs to be satisfied. Equation (33) accounts for the choice between the two modes for each trip request r.

$$tot_{cs} \leq VOT * \left(tt^{od_r}_{ground} - tt^{r}_{UAM} \right) \quad (29)$$

$$t^{ij}_{UAM} = tt^{od_r}_{ground} * \gamma_{\alpha} \quad (30)$$

$$t^{ij}_{UAM_{sp}} = t_{b_{aw}} + \frac{\operatorname{acos}\left(\sin(lat^{r}_{o}) * \sin\left(lat^{r}_{d}\right) + \cos(lat^{r}_{o}) * \cos\left(lat^{r}_{d}\right) * \cos\left(long^{r}_{d} - long^{r}_{o}\right) * R}{v_{UAM}} \quad (31)$$

$$ft^{ij}_{UAM} = \frac{1}{2}\left(t^{ij}_{UAM} + t^{ij}_{UAM_{sp}} \right) \quad (32)$$

$$\sum_{i} \sum_{j \neq i} a^{IJ}_{r} + g_r = 1 \quad (33)$$

3.4. Assumptions

Several assumptions have been made in this work, which are presented and briefly analyzed below to help the reader better interpret the results. This study considers both uncapacitated and capacitated scenarios regarding the number of aircraft a vertiport can serve. Although throughput and capacity are different concepts, there may be some confusion about what "aircraft served" and "capacity" mean in this context. It is assumed that static throughput applies to all vertiports, regardless of the area they cover, and that the number of aircraft served equals each vertiport's capacity. The authors acknowledge this as one of the study's limitations.

Moreover, while the value of time for potential passengers is considered in the formulations, their willingness to fly is not. Capturing and quantifying such a factor is challenging and would require, for example, a stated preference experiment. Nevertheless, this omission remains a limitation of the work. Although vertiport capacity is taken into account, aircraft/UAV parking capacity at vertiports is not considered separately, though it should be. It is assumed that after an aircraft lands at a vertiport, sufficient parking space is always available if no immediate demand exists.

Additionally, the demand for UAM services is assumed to remain constant throughout the considered time window, which overlooks the demand fluctuations during peak and off-peak hours. This could prevent evaluating the system's ability to handle varying demand volumes. The assumption of static demand also eliminates the need to reroute aircraft from a vertiport that cannot satisfy a demand request to the nearest available vertiport. Furthermore, unsatisfied demand is not included in the objective function. While charging/refueling times for eVTOLs and other aircraft types were considered, their monetary and temporal costs were not included in any of the objective functions.

Although different vertiport types and configurations, in terms of size, capacity, operational capabilities, and cost, are discussed in the literature, this work does not account for multiple vertiport types, nor does it include a sensitivity analysis of these parameters.

The service radius of each vertiport is assumed to be the same across all scenarios, whereas a variable service radius could offer more dynamic problem formulations. Specific regions have different demand volumes and customer locations, so adjusting this variable to meet regional demand and spatial profiles could provide valuable insights.

The vertiport locations identified by the clustering, genetic algorithm, and optimization models do not consider the spatial characteristics of these areas, such as the presence of other infrastructure that might prevent the construction of a vertiport. Additionally, the dimensions and land use requirements of a vertiport, as well as the noise and visual pollution impacts, are not accounted for. The effects on existing ground transportation systems are also overlooked.

4. Methodology Application

The proposed methodology was applied to the Chicago Metropolitan Area, accommodating a conceptual UAM service. Individuals' choices between ground and air transportation were assumed to be made based on the lowest generalized cost. While such an approach may not capture the individual preferences or specific characteristics of each mode, it can serve as a practical approximation, effectively assuming that individuals make rational decisions based on cost and time. For the secondary trip legs, two mode choice models were estimated. Note that our primary objective here is not to estimate demand, but rather to locate vertiports to serve a given demand pattern.

4.1. Data

TNC and taxi data from March 2019 for the Chicago Metropolitan Area [258,259] were used to estimate a demand profile for the conceptual UAM service introduced. If individual trips from these datasets fulfilled certain criteria (trip duration, distance), they were deemed eligible (similar approach to [6,20,25]).

A lower travel time bound of forty minutes [36,39] and a distance threshold of 17.5 miles [36,256] for a trip to be a UAM trip candidate were considered. After the filtering process, 11,603 TNC and 2107 taxi trips were found as candidate UAM trips.

In terms of software used, the various algorithms considered were coded in Python [283], using an Intel i7 2.80 GHz CPU processor, 64-bit Windows 10, and 16 GB RAM machine. Additionally, QGIS 3.16 was used for various spatial operations and graphical representations [284].

Additionally, spatial data regarding the heights of buildings in the Chicago Metropolitan Area, as well as the state of Illinois in general, were used [285]. It was found that there are 3158 buildings 400 ft tall or higher in the state of Illinois (with a median of 492 ft). In the area considered for this study, 121 out of the 3158 such buildings exist, with 116 of them being located within an approximately 1.9 square mile buffer area. Therefore, identifying vertiport locations within that area will require consideration of the restrictions created by the spatial output of the area under consideration.

4.2. Clustering Analysis

The following validity indexes were used to compare the two clustering models: the Akaike Information Criterion (AIC) [286], the Bayesian/Schwarz Information Criterion (BIC) [287], the Silhouette Score [288], and the Calinski–Harabasz and Davies–Bouldin indexes [289]. For the AHC algorithm, dynamic clustering was considered, with the number of clusters determined based on the dendrogram generated, with that number being thirteen. Additionally, the same fixed clusters number approach that was used in the k-means case was used here as well, and, based on the AIC and BIC metrics, eleven clusters, i.e., candidate facility locations, were found to be optimal. Following, Figure 3 presents the candidate locations (larger circles), with the demand request points (colored circles, with each color corresponding to its cluster center). Each colored points assembly represents a distinct cluster of demand request points, that are assigned to a common cluster center or service point, i.e., a facility location.

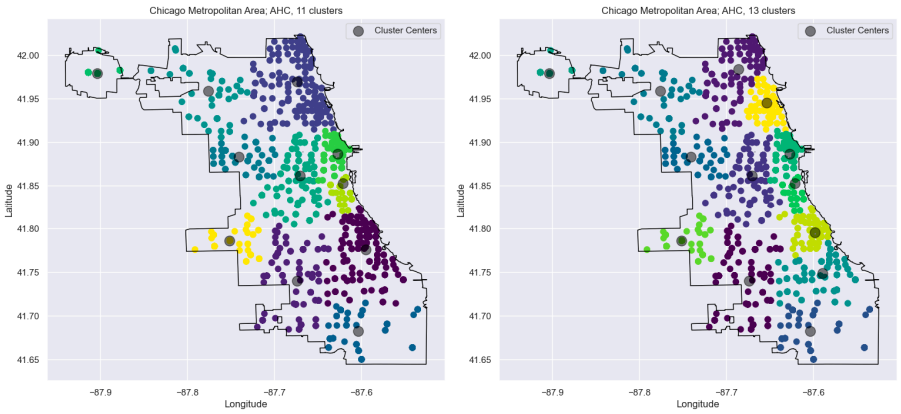


Figure 3. Agglomerative Hierarchical Clustering -based candidate vertiport locations.

Based on the Calinski–Harabasz and Davies–Bouldin indexes, the AHC model was preferred over the k-means model, and when the two AHC models were compared, the one with the thirteen clusters was slightly preferred, and it was, therefore, used as the generator of initial candidate locations for the following problem formulations.

4.3. Numerical Analysis

Of the 13,710 daily potential UAM trips, 3614 UAM trips were identified, based on generalized cost and travel distance criteria, for a 16 h time window. Each trip has an origin and a destination; therefore, an individual trip accounts for two operations, a take-off and a landing.

Results

Regarding the UVLP, since there are no capacity constraints, fewer facility locations were identified as necessary to cover the demand (100% coverage, since each facility can serve demand without an upper bound), with 15 and 14 facilities being found as the optimal solutions, in scenarios without and with initial candidate locations, respectively. When comparing the cases of having and not having candidate locations, the solution with candidate locations produced a lower average distance between demand points and their closest-in-proximity facilities (0.67 versus 1.24 miles), as well as a lower maximum distance of a demand point from its closest facility (1.52 versus 1.95 miles). In terms of computational time, it was slightly lower for the case with candidate locations (2785 versus 3026 s).

For the CVLP case, below the 0.93-mile service radius threshold, while such scenarios are closer to the 0.25- and 0.5-mile walkable distance thresholds [290,291], demand coverage dropped notably. Even if the number of vertiports was to increase significantly (by relaxing the budget constraint), the service radius could not be reduced adequately to approach the 0.25- and 0.5-mile walkable distance thresholds without exceeding a feasible number of vertiports. These results approximate the MCLP results presented next, with the difference that the GA shows higher demand coverage percentages for a similar service radius and numbers of vertiports, indicating that the proposed methodology can provide better results. While the CVLP is not the same problem as the evaluation FLPs, the common ground between objectives makes them good reference and evaluation tools. Also, when compared to the LCSP and *p*-median and *p*-center problems, the GA can lead to more favorable cases, in terms of the number of vertiports, average distances, and demand coverage. However, the GA is notably more computationally demanding than the MCLP, LCSP, and *p*-median problem. Figure 4 summarizes these results and extends them to different scenarios.

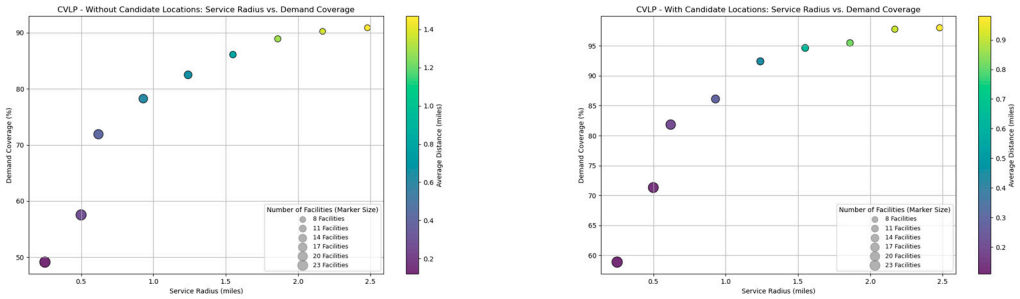


Figure 4. Capacitated Vertiport Location Problem without and with candidate locations results.

Regarding the evaluation FLPs, beginning with the MCLP, for smaller numbers of vertiports, and relatively small service radiuses, the demand coverage is below 85%, and goes down to approximately 55%, meaning that a significant portion of trip requests would be unserved. As expected, the higher the number of vertiports and the service radius, the higher the coverage. This can be observed in Figure 5 below, where for different numbers of vertiports, multiple radius scenarios were considered, providing a more comprehensive picture of the correlation between these parameters.

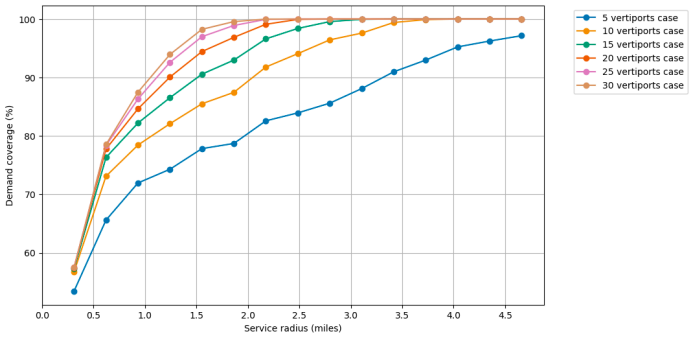


Figure 5. Demand coverage vs. coverage radius vs. number of vertiports.

The above observations can also be found on Figure 6, where the MCLP and LCFP analyses are presented. The service radius was found to play a key role, since with lower radius values, demand coverage is low as well. To the extent that the service radius is a metric of accessibility, accessibility is lower when the number of vertiports is small, and people would have to traverse a longer distance to reach their closest facility. This can be directly related to equity, since potential passengers could be excluded, when they cannot access this service with reasonable travel time, cost, and comfort. From Figure 5, it can be seen that for a one-mile service radius, achieving demand coverage above 90% is not feasible, even in the case of thirty vertiports, emphasizing the strong relation between demand coverage and service radius.

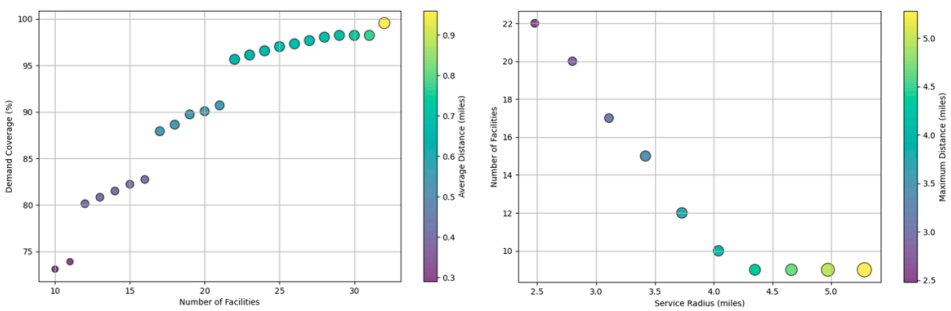


Figure 6. Maximum Coverage Location Problem sensitivity analysis (**left**), Least Service Coverage Problem sensitivity analysis (**right**).

Moving to the LCFP, Figure 6 summarizes the results for various scenarios considered, with the service radius being an integral aspect of this approach, since the problem was infeasible for several service radius values. Beyond a radius of approximately 2.5 miles, the problem is feasible, with higher radius values leading to a reduction in the number of facilities. As expected, the average distance of a demand request from the closest facility increases as the number of facilities is reduced. Convergence was attained in the case of nine vertiports, with radius values above 4.35 miles not being able to reduce the number of vertiports further. However, in terms of creating a network that emphasizes accessibility, this formulation does not offer a walkable distance service radius, since for even up to 2.17 miles (already well beyond a walkable bound), the problem was infeasible. In the results, the maximum distance corresponds to the farthest demand request from its closest facility.

In the case of the *p*-median problem, while the number of facilities increases, the mean distance between demand requests and their closest facility decreases. However, this problem formulation does not account for capacity, nor for service radius constraints; therefore, even though ten facilities can cover the demand, with a mean distance of less than 1 mile, there is a maximum distance of 5.81 miles. Even in the case of thirty-two vertiports, where the average distance is the lowest among other scenarios, there is a maximum distance of 2.98 miles. The former means that there will be potential customers that would have to cover that distance to access the UAM service, reducing its accessibility. As mentioned earlier, that may raise equity concerns, since a portion of potential passengers may be excluded from accessing this service. Flexible ride-hailing services may provide an alternative, albeit at a higher cost. Ensuring equitable access for all may be challenging under the constraints of such a problem formulation, with results presented in Figure 7.

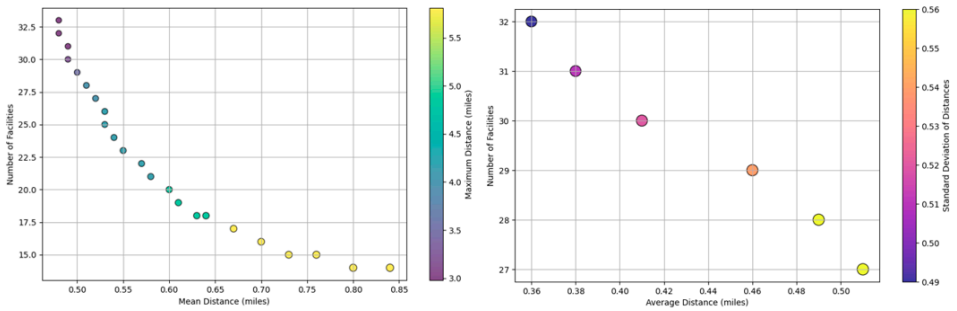


Figure 7. *p*-Median sensitivity analysis (**left**), *p*-center sensitivity analysis (**right**).

The *p*-center problem posed challenges in terms of computational time, as can be observed in Figure 7. Additionally, a sizable portion of the scenarios considered, especially those with a small number of facilities, were found not to converge on a solution. Since the primary objective of the problem is to locate facilities that minimize the maximum distance between a demand request and its assigned facility, and the formulation accounts for coverage of demand requests, the complexity of the problem increases significantly, even for relatively small datasets. As the number of facilities increases, both the average distance and the maximum distance have a decreasing trend, with the maximum distances providing promising results compared to previous methods, yet still significantly further from a walkable distance.

Each distinct shape in Figure 8 represents a specific scenario for a particular facility location problem (FLP). The shape circled with an orange circle corresponds to the solution of the CVLP with candidate locations, attempting to present the existence of this problem solution on the Pareto frontier, in a reader-friendly manner. This comparison illustrates the efficiency and effectiveness of various FLP methodologies, offering insights into the trade-offs between coverage, the number of vertiports, and average access travel time.

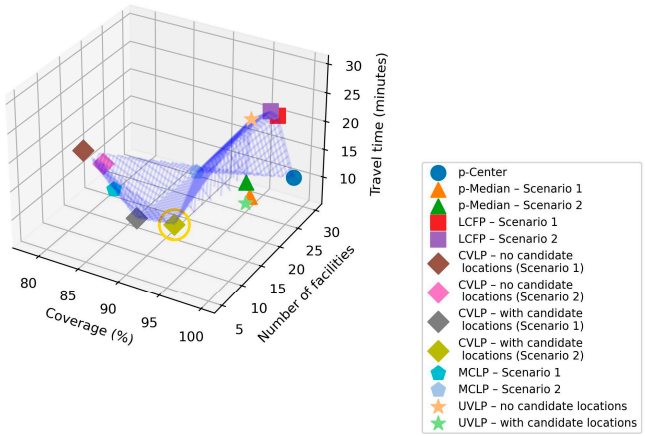


Figure 8. Comparison of Facility Location Problems' solutions (three-dimensional).

Below, Figure 9 illustrates selected scenarios from each considered FLP methodology in a two-dimensional space, comparing them in terms of demand coverage, the number of facilities, and the average travel time of a demand request to its nearest facility.

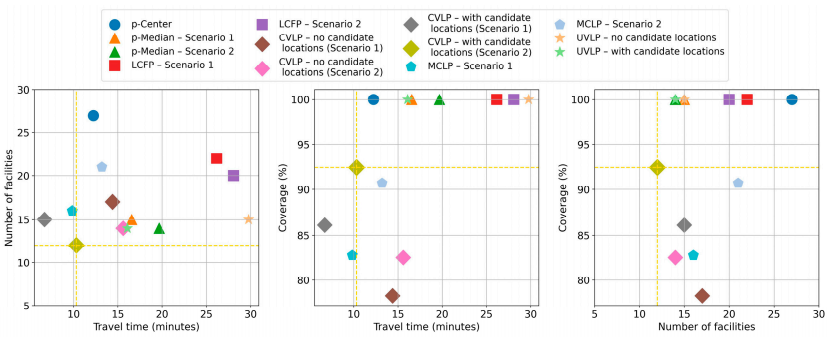


Figure 9. Comparison of Facility Location Problems' solutions (two-dimensional).

From Figure 9, the proposed problem formulation with capacity constraints (CVLP), solved by the developed framework, demonstrates the lowest average travel time for demand requests accessing the UAM service via a vertiport (yellow dotted horizontal and vertical lines were added for readability reasons). It achieves this with a reasonable number of vertiports relative to the number of facilities, also providing the lowest number of facilities while maintaining coverage above the 90% threshold. Consequently, this formulation and its solution (CVLP with candidate locations in Scenario 2) are positioned on the Pareto frontier.

One scenario for the MCLP (Scenario 2) is relatively close to this solution, with, however, an increase in average travel time and number of vertiports, lower coverage, and an increased number of facilities. Regarding coverage versus travel time, the *p*-center, *p*-median, and UVLP solutions provide 100% demand coverage with moderate average travel times, initially appearing promising. However, these methods lack capacity constraints, which leads to an unrealistic network design, assuming all demand requests will be served, and require a high number of vertiports (e.g., the *p*-center problem formulation identified a need for 27 vertiports).

The proposed framework and solution method (CVLP with candidate locations) can achieve a high coverage percentage (close to 93%) while keeping both the number of facilities and average travel time low. The MCLP solutions exhibit similar traits, albeit with increased numbers of facilities and travel times and slight decreases in demand coverage. Nonetheless, the two FLPs and their solution methods offer promising results for optimizing vertiport locations in terms of accessibility, coverage, and infrastructure cost.

To clarify comparisons, FLPs with and without candidate facility locations are presented separately in Figures 10 and 11, in two- and three-dimensional space, respectively.

Figures 12 and 13 compare FLP formulations that incorporate capacity constraints with those that do not. Notably, the proposed CVLP formulation is the only FLP examined that addresses capacity constraints.

Figure 14 presents a comparison of each FLP formulation, with the benchmark for each criterion (travel time, number of facilities, coverage). The FLP methodology with the superior solution on a given criterion is the benchmark. For travel time and number of facilities, the lowest value is the benchmark, while for coverage, it is maximum coverage. The proposed CVLP formulation and framework are on the high end (within the top three) in each criterion.

One can see that the FLPs without capacity constraints, and without candidate locations, have, on average, higher coverage percentages, which is a reasonable result since, without a capacity limit, a facility can serve as many demand requests as there are in its proximity. Additionally, higher average travel times can be observed since the locations of the demand requests are not taken into consideration. Therefore, the positioning of the facilities is not done with respect to where the demand is located. High travel times, even in cases with large numbers of facilities, can be the result of such instances. In general, full coverage comes at a high cost, as can be observed from the result tables and figures.

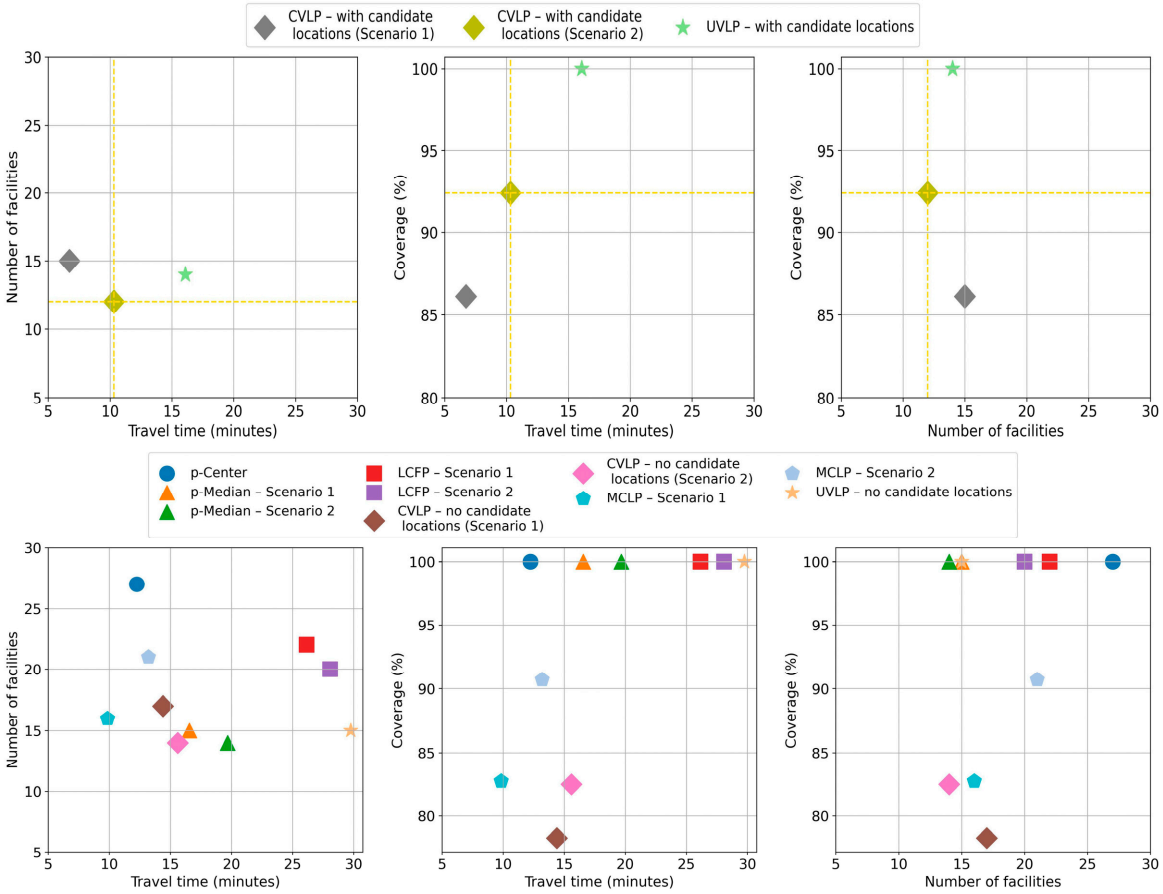


Figure 10. Comparison of Facility Location Problems' solutions with and without candidate locations (two-dimensional).

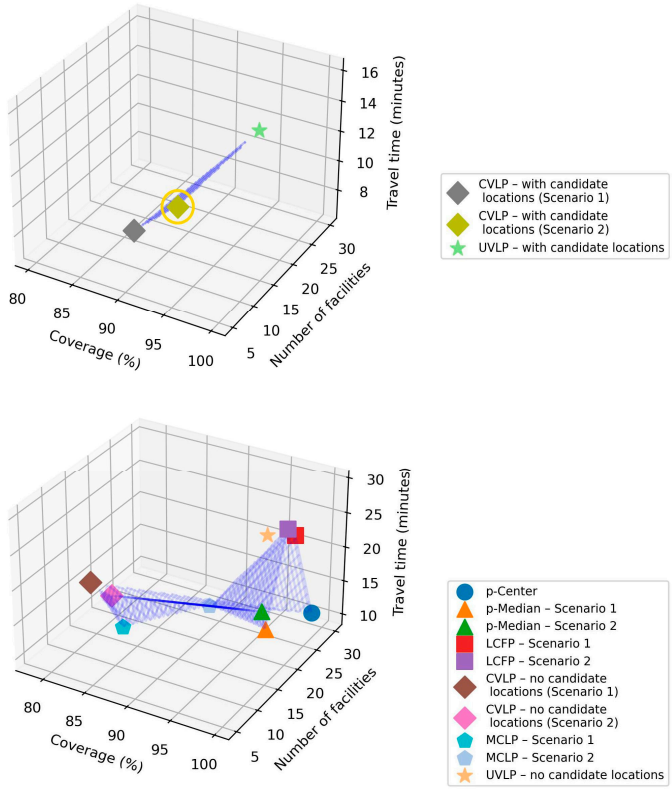


Figure 11. Comparison of Facility Location Problems' solutions with and without candidate locations (three-dimensional).

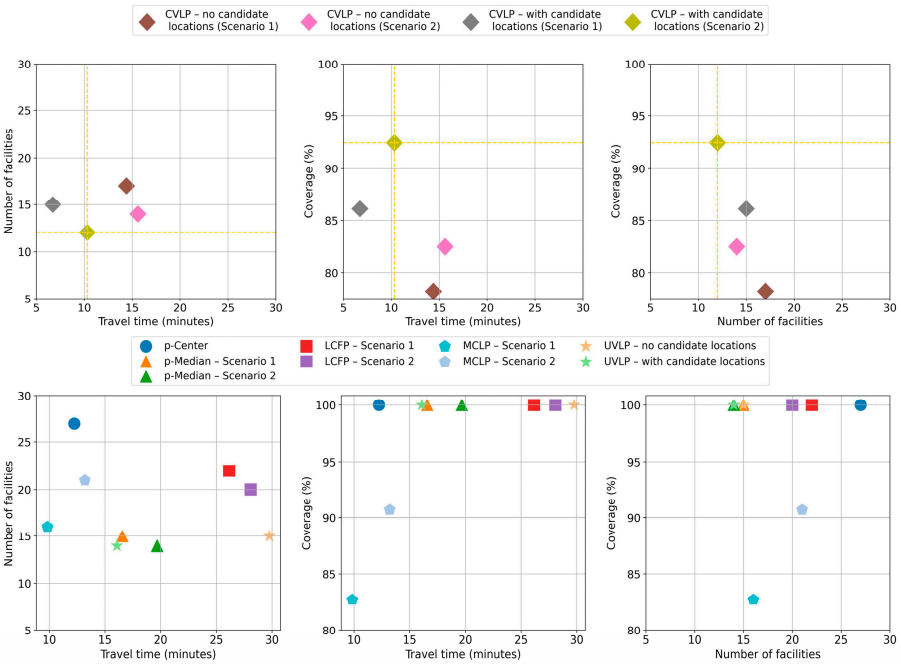


Figure 12. Comparison of Facility Location Problems' solutions accounting for capacity constraints (two-dimensional).

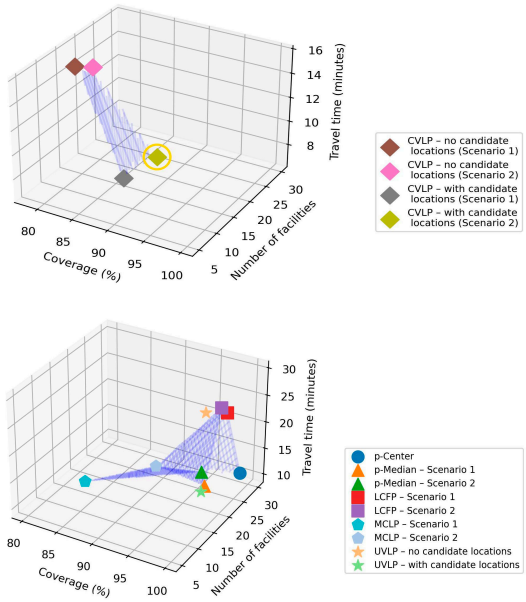


Figure 13. Comparison of Facility Location Problems' solutions accounting for capacity constraints (three-dimensional).

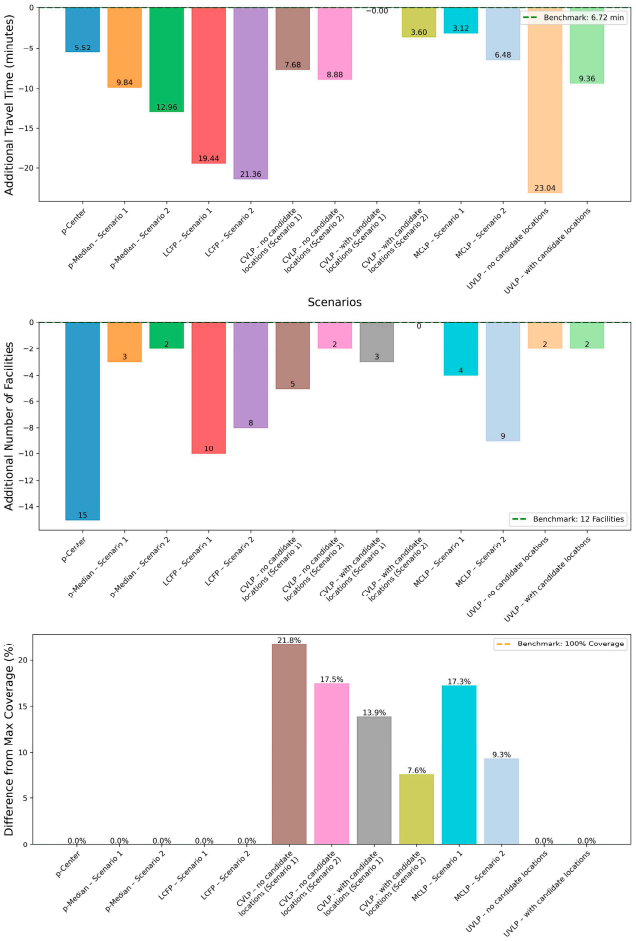


Figure 14. Comparison of Facility Location Problems' with benchmark values.

5. Conclusions

A concluding discussion summarizing the methods, formulations, and results from the application is presented. Additionally, limitations and future steps are discussed.

5.1. Discussion

Advanced Air Mobility (AAM), and specifically urban air mobility (UAM), focuses on incorporating aerial transportation systems into urban settings. This is envisioned to be accomplished with the use of non-electric and electric Vertical and Short Takeoff and Landing aircraft (VTOLs/eVTOLs and STOLs). The identification of optimal locations for take-off, landing, refueling/recharging, and parking sites for these aircraft is a major task. These operations are envisioned to take place at locations called vertiports or skyports.

Strategic infrastructure placement that minimizes travel time and maximizes accessibility and demand coverage, among other objectives, is of paramount importance. Two problem formulations are introduced in this work: the Uncapacitated Vertiport Location Problem (UVLP), and the Capacitated Vertiport Location Problem (CVLP). These are variations of the traditional Uncapacitated and Capacitated FLPs (UFLP and CFLP). The goal is to determine the optimal number and locations of vertiports needed to serve a demand area.

To solve these problems, a framework with two main steps was introduced. In the first step, an Agglomerative Hierarchical Clustering model was used to identify initial candidate vertiport locations, based on an estimated UAM for the given service area. The second step includes a genetic algorithm (GA), formulated in this work, which utilizes these candidate locations, and solves the UVLP and CVLP.

Additionally, to compare and evaluate the proposed methodology, a set of FLPs from the literature were adapted. Linear and integer programming, along with a heuristic approach, were used as solution methods for the evaluation set of FLPs. These problems were the Least Service Coverage Problem (LSCP), the Maximum Coverage Location Problem (MCLP), the p-median problem, and the p-center problem. The LSCP aims to find the minimum number of facilities required to ensure every demand area is within a predefined maximal service catchment area, measured in time or distance. The MCLP focuses on maximizing the demand covered within a maximal service distance or time window by placing a fixed number of facilities. The p-median problem is equivalent to a UFLP without budget constraints but with an upper limit on the number of facilities, whereas the p-center problem involves locating p identical facilities to minimize the maximum distance between demand points and their nearest facilities.

Based on the results for the Chicago area, the proposed framework for solving the UVLP and CVLP provided superior solutions compared to other methods. Although the evaluation set of FLPs included different FLPs than the UVLP and CVLP, they shared similar objectives, such as demand coverage and infrastructure accessibility. Therefore, their comparison was enabled. It was found that achieving demand coverage levels between 85% and 90% is feasible, with relatively low average access travel time and a reasonable number of vertiports to support such a network. Approaching the vertiport placement problem as an FLP with coverage and accessibility objectives is a promising direction for future investment in UAM. This is due to the fact that these problems and their formulations allow for a clear assessment of existing trade-offs. Additionally, it became evident that satisfying more than 90% of demand requests for such a UAM service significantly increases infrastructure costs. Additionally, it also requires a compromise in terms of reduced average travel time and distance benefits to accommodate more demand.

Regarding candidate location identification, clustering algorithms seem to identify locations that are well aligned with the distribution of demand points. However, these algorithms do not account for an upper bound of requests that can be served by a vertiport location. Therefore, they usually provide a lower number of facility locations than would be needed for a UAM network to operate in an access-inclusive manner. As seen from the solutions of the evaluation set of FLPs, such scenarios with ten, eleven, and even nine vertiports are feasible, but are followed by a certain social cost. Average distances between

customers and their closest facility greater than one mile, with maximum distances of three to five miles, can lead to equity-related issues. This may exclude a portion of potential customers who cannot travel such distances, thereby limiting their access to a vertiport.

In both the UVLP and CVLP cases, providing the GA with initial candidate locations improved the solution significantly, in terms of the utilization of each vertiport (serving as many demand requests as possible). Better spatial placement of the facilities is also achieved, leading to a lower average distance that demand points have to cross to their nearest facility. The proposed CVLP formulation, when solved with the proposed framework, can provide solutions that fall on the Pareto frontier with respect to average travel time, number of facilities, and coverage.

Regarding the evaluation set of FLPs, a common finding was the significant impact that the service radius has. Lower service radius values correspond to limited demand coverage. However, an increase in radius may lead to reduced accessibility, especially when the number of vertiports is low. This raises concerns in terms of equity, as some individuals may be unable to access a facility under reasonable distance assumptions. Specifically, for the MCLP, when the number of vertiports is small and the service radius is relatively low, demand coverage drops significantly. This indicates that a considerable portion of trip requests will go unserved. As anticipated, an increase in both the number of vertiports and the service radius leads to higher coverage. It became evident that maintaining demand coverage above 90% is not achievable below the threshold of a one-mile service radius. The results of the LSCP showed that if the service radius in the perimeter of each vertiport falls below 2.2 miles, the problem becomes infeasible (for the given dataset). Lower bounds of twenty-two vertiports and a 2.48-mile service radius were found to be feasible for the problem. In the context of the *p*-median problem, as the number of facilities increases, it is logical to observe a decrease in the mean distance between demand requests and their closest facility. However, that problem formulation lacks considerations for capacity and service radius constraints. Consequently, even if few facilities can adequately cover the demand with a mean distance of less than 1 mile, a maximum distance constraint of 5.81 miles raises equity considerations. The *p*-center problem required more computational time to converge, and its solutions included a relatively high number of vertiports (above 26 facilities).

The proposed framework and problem formulation contribute to the facility location problem literature within the context of UAM. By comparing the proposed capacity-constrained vertiport location problem (CVLP) with other FLPs, the framework demonstrates its effectiveness in achieving a high demand coverage while minimizing the average travel distance and the number of facilities needed. Unlike traditional formulations that do not account for capacity constraints, the proposed method effectively balances accessibility and infrastructure costs. The results indicate that the CVLP formulation is positioned favorably on the Pareto frontier, highlighting its potential as a benchmark for future research and applications in the field. Overall, this work highlights the importance of capacity constraints in facility location problems, as it not only ensures realistic network solutions, but also paves the way for more efficient and sustainable urban mobility systems.

5.2. Limitations and Future Steps

This study has provided an approach for the strategic exploration of the extent and location of vertiport infrastructure at a metropolitan area level. Several aspects of the methodology and its application to a specific area could be improved, including the following:

- More detailed spatial and land use data are required to adequately assess the identified locations. Considerations should include the existing air infrastructure, spatial limitations, and safety, noise, legal, and legislative issues.
- The impact on the existing transportation network from the construction of vertiports is not accounted for (e.g., congestion in the ground network near vertiport locations and changes in travel patterns).

- While the use of TNC and taxi data provides useful insights, the absence of trips made by other modes in the dataset is a limitation.
- The lack of dynamically changing demand precludes rerouting strategies for aircraft.
- Passengers' willingness to fly was not considered, which is a critical factor in the adoption of urban air mobility. This omission limits a comprehensive understanding of user behavior and preferences.
- Vertiport parking capacity was not considered, although a more complete problem formulation should include this parameter as an individual aspect and constraint.

Several future directions could be pursued to extend and enhance this work. One important avenue from a public policy perspective is to explore how the development of UAM services can address equity issues. Another key area is to assess the impact of noise, which is a social impact that eVTOLs and STOLs could potentially impose. The effect of UAM services on existing transportation networks and the resulting social implications are of high importance. An evaluation of land use, regulatory, and safety restrictions regarding the optimal locations found is also something that will be pursued as a next step.

Accounting for additional objectives within the optimization framework is also crucial, as the vertiport location problem involves multiple, often conflicting, objectives, such as demand coverage, service accessibility, and network cost minimization. This paper focuses on comparing results generated by different methods and examining the trade-offs involved in various solutions.

Although the GA implemented in this study has proven effective, expanding the methodological approach could offer valuable insights and potentially lead to better solutions. Exploring alternative heuristic methods is one option, and even more insightful could be the application of exact methods for the UVLP and CVLP, enabling further comparison of solution techniques.

Additionally, considering dynamically changing demand, the likelihood of trip cancellations, the inability to meet requests, and the need for rerouting to nearby vertiports are equally key factors to address.

Finally, integrating UAM services with existing public transportation networks to create a seamless multimodal system is another desirable step. Evaluating the feasibility of establishing intermodal hubs that connect UAM services with public transportation modes such as buses and trains could reduce inequality in accessibility and enhance passenger convenience.

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Conflicts of Interest: The authors declare no conflicts of interest.

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