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A Capacitated Set Cover Formulation for Vertiport Location and Air Taxi Allocation

Zahra Zare
Graduate Student
Department of Industrial and Human Factors Engineering
Wright State University, Dayton, OH, USA
zare.3@wright.edu

Mumtaz Karatas
Associate Professor
Department of Industrial and Human Factors Engineering
Wright State University, Dayton, OH, USA
mumtaz.karatas@wright.edu

Yu-Jun Zheng
Professor
Affiliated Hospital of Hangzhou Normal University,
Hangzhou Normal University, Hangzhou, 310015, China
School of Information Science and Technology,
Hangzhou Normal University, Hangzhou, 311121, China
yujun.zheng@computer.org

Abstract

The rapid advancement of Urban Air Mobility (UAM) presents new challenges in the strategic placement of vertiports and the efficient allocation of air taxis to these vertiports. In this study, we formulate a mathematical model based on the capacitated set cover model to determine the optimal vertiport locations as well as the number of air taxi allocations while minimizing total infrastructure and operational costs. Our formulation integrates constraints on fleet size, vertiport capacity, and demand coverage to ensure an efficient UAM network which can satisfy the demand in a given region of interest. We demonstrate the applicability of our modeling approach on a case study for the southwest region of Ohio, USA and perform several numerical experiments using real-world population data and varying demand scenarios to analyze the impact of operational range and demand percentage on network configuration. Our findings for the case of Ohio highlight the trade-off between infrastructure investment and operational effectiveness in UAM planning.

Keywords
Urban Air Mobility, Capacitated Set Cover Problem, Vertiport Location, Resource Allocation, Optimization

1. Introduction
Urban Air Mobility (UAM) is a solution to reduce congestion, enhance regional connectivity, and streamline last-mile transportation in urban and suburban settings (Holden and Goel, 2020). One of the major issues with implementing UAM systems is strategic planning of vertiport locations and air taxi fleets to ensure comprehensive service coverage

and maintain operational and financial efficiency. Traditional facility location problems, such as the Maximal Coverage Location Problem (MCLP), or the classical Set Cover Problem (SCP), have been employed for decades in location planning in various contexts such as healthcare, energy, defense, supply chain, transportation, etc. (Daskin, 2013).

The problem of vertiport location planning and resource allocation has attracted attention in the last decade. Several researchers tackled the problem of vertiport placement to improve accessibility and service performance with various modelling approaches. In this study, different from previous work on UAM planning, we propose a combined location and allocation optimization model that relies on a set cover modelling framework to locate capacitated vertiports and allocate air taxis to these vertiports to ensure that the demand in the region of interest if fully satisfied. The formulation we propose aims to minimize the total cost of locating vertiports and the total operational cost of allocating air taxis. In other words, we pose our modelling framework as a variant of the classic SCP model that accounts for capacitated facilities and resource allocation. This is reflective of a more realistic planning context that is aligned with both infrastructural investment ambitions as well as day-to-day operational imperatives (Macias et al., 2023).

We also note that, the problem we tackle in this study comprises of a strategic level decision of vertiport location planning as well as a tactical level problem of air taxi allocations. Among the key factors that impact the former, accessibility (or service coverage) is one of the most critical. In location science, accessibility is typically evaluated based on the distance between a facility and the customers or demand centers it serves. Coverage models are widely used in the literature as they enable decision-makers to quantify service levels and assess the extent of demand coverage. In the rich body of location science literature, various types of coverage models exist, each with distinct objectives. For instance, in the MCLP, the objective is to maximize the amount of demand covered given a fixed amount of resources, whereas in the SCP, the goal is to minimize the number of facilities required to ensure full demand coverage.

Since the concept of UAM and air taxis is still emerging, we believe that the SCP approach is a better fit due to its focus on ensuring essential coverage with minimal infrastructure investment. In the early stages of UAM deployment, where demand patterns are uncertain and infrastructure budgets are limited, SCP models allow planners to strategically identify a minimal set of vertiport locations that can serve all demand points within a predefined coverage radius. This helps reduce initial capital costs while maximizing accessibility and system reach. Furthermore, the capacitated extension of the SCP adds realism by incorporating limits on the number of air taxis each vertiport can host, reflecting real-world constraints such as land availability, air traffic, and operational throughput. For the tactical problem of air taxi allocation, we believe that the capacitated set covering model provides a practical and flexible framework for assigning limited resources while ensuring regional accessibility. Unlike purely strategic models that focus only on facility siting, this approach captures the day-to-day operational challenge of determining how many air taxis to allocate at each vertiport, considering both demand coverage and capacity constraints.

Implementing a variant of the SCP formulation with capacitated facilities and resource allocations, we propose an integer linear programming (ILP) formulation and demonstrate its applicability on a real-world case study for the southwest region of Ohio, USA. In particular, we utilize actual population data at the county and city levels in Ohio, along with intercity distances, as proxies for demand and travel distance. Our model integrates spatial constraints, vehicle range limitations, vertiport capacities, and air taxi capacities to ensure both coverage and feasibility.

The structure of the paper is as follows: In Section 2 we present the related work on vertiport location models in the context of UAM. In Section 3, we introduce the combined location and allocation mathematical model for the vertiport/air taxi planning problem. In Section 4, we provide the details of our case study for Ohio State. Finally, in Section 5, we conclude and suggest directions for potential future research.

2. Literature Review

In this section we review the related work that lies in the intersection of facility location, resource planning, and urban air mobility. Since there exists a rich body of literature on these domains, we focus on studies which consider the simultaneous vertiport location and air taxi fleet optimization decisions.

The SCP is a fundamental NP-hard combinatorial optimization problem where the goal is to find the smallest collection of sets from a given family whose union covers a universe of elements (Caprara et al. 2000). This problem arises in applications like resource allocation, facility location, and network design. It has been applied to several real-world cases including scheduling, manufacturing, service planning, information retrieval, etc. (Lan et al. 2007). A classic example involves hiring the fewest programmers to cover all required programming languages, where each programmer represents a set of languages they know. The capacitated SCP extends the classical framework by introducing capacity constraints on the sets. This models real-world scenarios with resource limitations, such as constrained server capacities in network coverage or budget limits in workforce allocation. For example, in capacitated vertex cover, each vertex can cover only a limited number of edges, and multiple copies of a vertex may be used up to a specified limit.

Several studies have explored set cover-based location models or variations such as *p*-hub, maximal covering, and capacitated location problems. Among those studies, Macias et al. (2023) proposed a three-stage model integrating vertiport location, air taxi vehicle sizing, and infrastructure capacity. The authors highlighted the risks of neglecting battery range and queuing in UAM network design. Vicencio-Medina et al. (2023) extended the MCLP by incorporating accessibility measures and mobile stations, achieving a balance between service coverage and equity through a matheuristic approach. In a more cent study, Volakakis and Mahmassani (2024) compared standard facility location models, including SCP, MCLP, *p*-median, and *p*-center, in determining equitable vertiport locations, developing multi-objective formulations and solution heuristics. Jin et al. (2024), on the other hand, applied robust optimization to vertiport location selection while considering travel mode choices under demand uncertainty. Kitthamkesorn and Chen (2024) formulated a multi-allocation incomplete *p*-hub location problem to address the maximum capture problem in UAM network design, incorporating constraints related to vehicle flying range and urban coverage. As another important study in the domain of UAM planning, Yue Yu et al. (2023) modeled vertiport selection as a mixed-integer equilibrium problem. The authors proposed an optimization framework for reduced congestion in hybrid air-ground networks.

Vertiport location optimization is among the central topics in planning UAM. As an example study, Hess et al. (2024) utilized a MCLP formulation for binary and probabilistic coverage models to determine the optimal locations of vertiports in Ohio state. In another similar study for Ohio, Mandava and Karatas (2024) posed the vertiport location problem as an Uncapacitated Hub Location Problem with Single Assignments Hub Location Problem (UHLPSA). In their proposed formulation the authors aimed at minimizing the total transportation cost across the network. Petit and Ribeiro (2025) presented a multi-objective middle-mile vertiport location model that balances land use, safety, and demand coverage. Hagspihl et al. (2025) presented a choice-based demand model for airport shuttle networks, with a focus on interdependencies between vertiport location and passenger choice. Onat et al. (2023) designed VertiSim, a simulation platform that replicated how fleet size and vertiport spacing affected delay, utilization, and energy consumption within UAM networks. Taken together, these studies demonstrated that vertiport location decision must be closely coupled with operational metrics and user demand behavior.

Fleet planning is another fundamental problem in UAM operations. Fleet size planning, scheduling, resource allocation are some of the sub-topics investigated by researchers. Among those studies, Lindner et al. (2024) presented an optimization approach for determining air taxi fleet sizes and utilized a discrete-event simulation model. The authors examined the effects of vehicle routing and scheduling under operational constraints. Sun et al. (2023) proposed a fairness- and risk-averse allocation model incorporating airspace capacity, passenger demand, and network resilience to disruptions. These papers showed how under- or overestimation of fleet requirements could significantly affect service quality, cost, and system robustness.

There also exist studies which propose combined systems that integrate strategic level facility location with dynamic operational level decisions. Among these studies, Krisshna Kumar et al. (2023) used a graph reinforcement learning technique to perform scheduling in real-time for vertiports, such as pad conflict and aircraft sequence. Macias et al. (2023) and Yue Yu et al. (2023) offered multi-stage models and mixed integer linear programming (MILP) based formulations, respectively. These studies integrated several decisions such as vertiport location, resource allocation, sizing, and congestion mitigation.

Our study contributes to the existing literature on location science and UAM planning by bridging the gap between strategic facility location and tactical resource allocation. Unlike traditional SCP-based location models, our approach explicitly incorporates capacity constraints for both vertiports and air taxis, providing a more realistic representation of infrastructure limitations and operational feasibility. Additionally, by applying our model to a real-world case study in southwest Ohio, we demonstrate its practical applicability and effectiveness in guiding UAM planning. We believe that this work advances the field by offering an integrated framework with real life limitations that balances cost efficiency with service coverage.

3. Methods

In this section, we present our proposed mathematical formulation for the combined location and allocation optimization model for vertiport placement and air taxi fleet distribution. Specifically, we introduce an ILP formulation approach that adapts the classic SCP which assumes capacitated vertiports and air taxis. Our model aims to minimize the total cost of establishing vertiports and the operational costs of allocating air taxis, while ensuring full service coverage across the region. Below, we define the sets and indices, parameters, decision variables, and full formulation.

Sets and Indices

$i, j \in I$: Set of demand nodes and potential vertiport locations.

Parameters

F_i: Cost of establishing a vertiport at location i ($).
H : Capacity of each air taxi (number of people it can serve within a planning horizon).
K_i^{min}, K_i^{max}: Minimum and maximum number of air taxis that can be assigned to vertiport i.
P_i : Population demand at node i.
α : Percentage of total population using air taxis.
C : Cost per air taxi ($).
r : Coverage radius of a vertiport (miles).
a_{ij}: Binary parameter, 1 if demand node i is within coverage range r of vertiport j, 0 otherwise.

Decision Variables

$x_i \in \{0,1\}$: 1 if a vertiport is established at location i, 0 otherwise.
$y_i \in \mathbb{Z}$: Number of air taxis assigned to vertiport i (integer).
$z_{ij} \in \{0,1\}$: 1 if demand node i is covered by vertiport j, 0 otherwise.

The objective function minimizes the total cost of building vertiports and allocating (deploying) air taxis. The first term represents the total cost of vertiports, while the second term accounts for the cost of air taxis.

$$\min \sum_{i \in I} (F_i x_i + C y_i)$$

The following constraint ensures that each demand node is covered by at least one vertiport within its range. Note that a_{ij} is a binary matrix that is preprocessed to indicate whether a demand node *i* is covered by a vertiport located at *j*.

$$\sum_{j \in I} a_{ij}\, z_{ij} \geq 1 \,, \forall i \in I$$

The next constraint guarantees that a demand node *j* can only be assigned to a vertiport at location *i* only if that vertiport is established.

$$z_{ij} \leq x_j \,, \forall i, j \in I$$

The following constraint ensures that the total population covered by a particular vertiport must be served by the assigned air taxis. In the constraint, the left-hand-side represents the total demand covered by a vertiport at *j*, whereas the right-hand-side represents the total weekly capacity of the air-taxis stationed at that particular vertiport.

$$\sum_{i \in I} \alpha P_i\, z_{ij} \leq H y_j \,, \forall j \in I$$

The following constraint ensures that each vertiport *i* can accommodate at least K_i^{min}, and at most K_i^{max} air taxis.

$$K_i^{min} x_i \leq y_i \leq K_i^{max} x_i \text{ , } \forall i \in I$$

The following constraint sets define variable domains.

$$x_i \in \{0,1\}, \forall i \in I$$

$$z_{ij} \in \{0,1\}, \forall i, j \in I$$

$$y_i \in \mathbb{Z} \text{ , } \forall i \in I$$

4. Case Study for Ohio: Numerical Results and Discussion

In this section, we present the numerical results we obtained from applying our proposed optimization model to the case study in the southwest region of Ohio. In the first subsections we provide an overview of the case study data, and relevant operational parameters such as vehicle range and vertiport capacities. In the second subsection, we present the numerical results derived from the model, including key performance metrics, such as the optimal number and locations of vertiports, air taxi allocation plan, and resulting costs.

4.1 Case Study Data

We applied our capacitated set cover and resource allocation modeling approach to a case study involving 50 selected cities in the southwest region of Ohio, USA. This region includes several highly populated metropolitan areas, such as Cincinnati and Dayton, along with many rural towns and communities. The region also has a well-developed highway network, which is vital for commerce and transportation within the state.

The total population of the 50 cities in our case study is 1,384,365, with an average city population of 27,687 and a standard deviation of 46,400. The smallest city, St. Bernard, has a population of 4,368, while the largest, Cincinnati, has 309,317 residents. The average distance between cities is 32.29 miles, with distances ranging from 1.17 miles to 84.38 miles. Figure 1 displays the southwest region of Ohio we considered in our case study analysis.

For our numerical experiments and computational runs, we implemented our formulation in the General Algebraic Modeling System (GAMS) and solved the instances using the commercial solver CPLEX 22.1.0. Computations were performed on a computer with an Intel(R) Core(TM) i7-11800H @ 2.30 GHz processor and 16 GB of RAM.

The cost of constructing a modular vertiport is estimated to be between \$800,000 and \$1 million (aviationweek.com). The approximate cost of a self-flying electric air taxi is around \$330,000 (flyingmag.com). In our case study, we assume fixed costs of F_i =\$800,000 for each vertiport located at location *i* and $C =$ \$330,000 for each air taxi. Since empirical data on air taxi adoption rates is limited, we assume that between 1-2% of the total population would use the service. Based on this assumption, and without loss of generality, we set the weekly (planning horizon) capacity of each air taxi at $H = 500$, representing the approximate number of passengers an air taxi can serve per week. Since all vertiports are assumed to be of the same type, we set a fixed minimum and maximum capacity of $K_i^{min} = 3$, and $K_i^{max} = 15$ air taxis per vertiport, respectively.

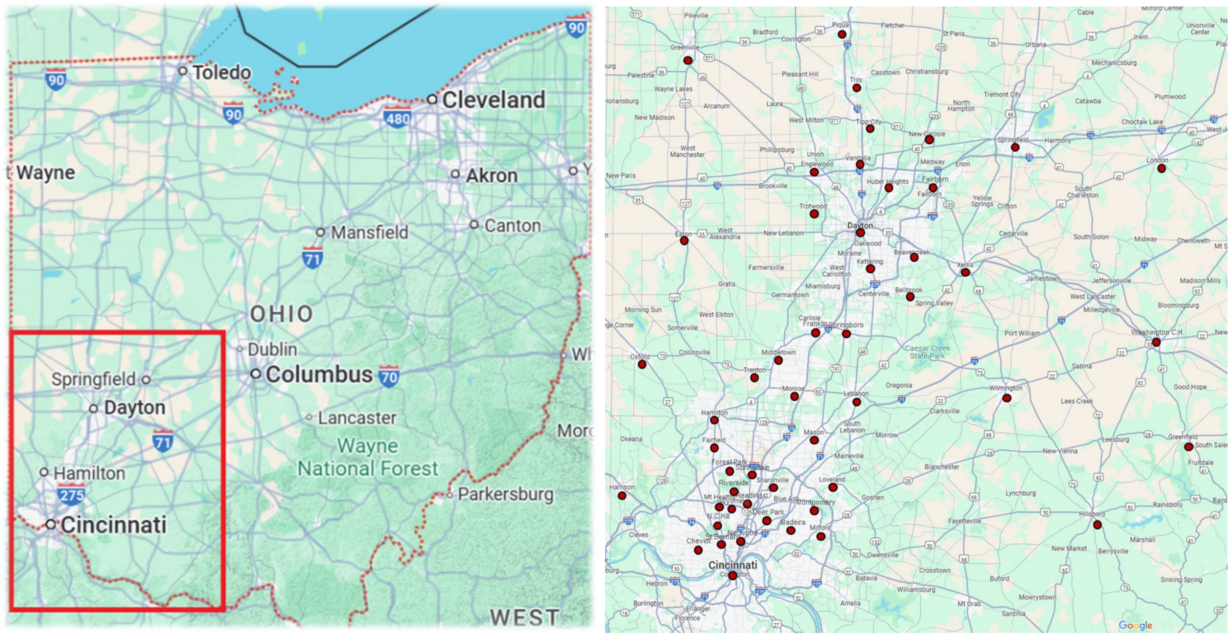

Figure 1. Southwest part of Ohio, USA

We conducted numerical experiments for varying demand percentages $\alpha = \{1\%, 1.5\%, 2\%\}$ and operational ranges $r = \{10,15,20\}$ miles. This resulted in nine different runs, each corresponding to a unique combination of demand percentage and range pair denoted as (r, α).

4.2 Numerical Results

In Table 1, we report the results of different air taxi network configurations based on varying demand percentages and operational ranges. The objective function value in the second column represents the total cost in millions of dollars for building the required vertiports and acquiring air taxis. The results show that as the demand percentage increases, the overall cost rises due to the need for additional air taxis and, in some cases, more vertiports. For example, when the operational range is 10 miles, increasing the demand from 1% to 2% raises the number of air taxis from 58 to 82, with the number of vertiports remaining relatively stable at around 17–18.

As expected, the operational range *r* also has a significant impact on the number of vertiports and total cost. As the range increases, fewer vertiports are needed since air taxis can serve broader areas. This is evident when comparing the results at 1.5% demand: the number of vertiports drops from 18 at 10 miles to 7 at 20 miles, and the cost decreases from \$36.00M to \$20.30M. However, the number of air taxis remains relatively high across different ranges (e.g., 61 at *r* = 20 miles), indicating that although fewer vertiports suffice with extended range, additional vehicles are still needed to satisfy higher demand levels. This suggests that longer operational ranges help reduce infrastructure costs, but effective fleet coordination remains essential to maintain service quality.

The table also reveals a trade-off between infrastructure investment and operational efficiency. A higher number of vertiports ensures better distribution of air taxis but increases total costs. On the other hand, relying on fewer vertiports with longer-range air taxis reduces infrastructure costs but may introduce logistical challenges. The choice of operational parameters should balance cost efficiency with practical considerations to ensure a sustainable and well-functioning air mobility network.

Table 2, on the other hand, presents in which cities the vertiports should be built and how air taxis should be allocated across different cities for each scenario. The table also provides insight into how demand and operational range influence distribution patterns. The results show considerable variation in allocation depending on the scenario, with some cities consistently receiving taxis while others do not.

Table 1. Summary of the numerical results

Instance (r, α)	Obj. Func. Value ($M)	Total # of Vertiports	Total # of Air Taxis
(10, 1%)	31.00	17	58
(10, 1.5%)	36.00	18	72
(10, 2%)	38.20	17	82
(15, 1%)	22.90	11	47
(15, 1.5%)	27.10	11	48
(15, 2%)	30.70	11	73
(20, 1%)	16.10	7	35
(20, 1.5%)	20.30	7	49
(20, 2%)	24.70	8	61

Table 2. Vertiport locations and allocation of air taxis to cities for each problem instance

Instance	Beavercreek	Bellbrook	Cheviot	Eaton	Fairborn	Fairfield	Forest Park	Greenfield	Greenville	Hamilton	Harrison	Hillsboro	Lebanon	London	Loveland	Maderia	Mason	Middletown	Milford	Monroe	Montgomory	Mount Healthy	New Carlisle	North College Hill	Oxford	Sharonville	Springboro	Springfield	Tipp City	Trenton	Troy	Vandalia	Washington Court House	Wilmington	Wyoming
(10, 1%)	5	0	0	3	0	3	0	3	3	0	3	3	0	3	0	0	0	3	0	0	3	0	0	0	3	0	0	3	0	0	3	4	0	3	7
(10, 1.5%)	5	0	0	3	0	0	0	3	3	0	3	3	0	3	3	0	0	0	3	0	0	13	0	0	3	0	4	3	0	3	3	8	3	3	0
(10, 2%)	14	0	0	3	0	0	0	3	3	3	3	3	3	3	0	0	0	0	0	0	4	0	0	0	3	0	0	3	0	0	0	5	3	3	15
(15, 1%)	0	0	10	3	8	0	0	0	3	4	0	3	0	3	0	0	3	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	3	3	0
(15, 1.5%)	0	0	0	3	0	12	14	0	3	4	0	3	0	3	0	0	7	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	3	3	0
(15, 2%)	0	0	0	3	9	0	0	0	3	5	0	3	0	3	0	0	0	0	0	12	0	15	0	0	0	0	0	0	14	0	0	0	3	3	0
(20, 1%)	0	6	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	11	0	5	0	0	3	0	0	0	0
(20, 1.5%)	0	5	0	0	0	15	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	4	0	0	0	13	0	0	0
(20, 2%)	0	15	0	0	0	0	0	3	3	0	0	0	0	0	0	6	0	0	0	0	0	0	5	15	6	0	0	8	0	0	0	0	0	0	0

Larger cities such as Cincinnati (309,317), Dayton (137,644), and Hamilton (62,082) naturally appear as key candidates for air taxi services due to their size and potential demand. However, Cincinnati and Dayton, despite being the large cities, receive no taxis in any of the instances. This indicates that factors such as spatial positioning within the network and operational constraints outweigh raw population in determining allocation. In such cases, vertiports may still be located nearby, allowing these high populated cities to be serviced indirectly within range limits.

The table reveals that Greenville plays a central role in the network design as it is the only city that receives a nonzero air taxi allocation in all nine instances. This suggests that it serves as a strategic hub for maximizing regional coverage efficiently. Other cities such as Eaton, Greenfield, Hillsboro, London, and Springfield also appear in a majority of the solutions (6 out of 9), showing their value as secondary hubs or as cost-effective locations for expanding coverage. Interestingly, Cheviot, Forest Park, Madeira, Middletown, Milford, Monroe, New Carlisle, North College Hill, Sharonville, and Trenton each appear in only one of the nine solutions. This likely reflects their limited marginal benefit in the network, either due to overlapping coverage with more central locations, or low standalone demand. These infrequent selections may also be a result of tight capacity constraints in the model, where prioritizing other sites yields higher system-wide coverage. In Figure 2 and Figure 3 we display the optimal vertiport locations and the number of air-taxis allocated to each vertiport for $r = 15$ miles and $\alpha = 2\%$, and $r = 20$ miles and $\alpha = 2\%$, respectively.

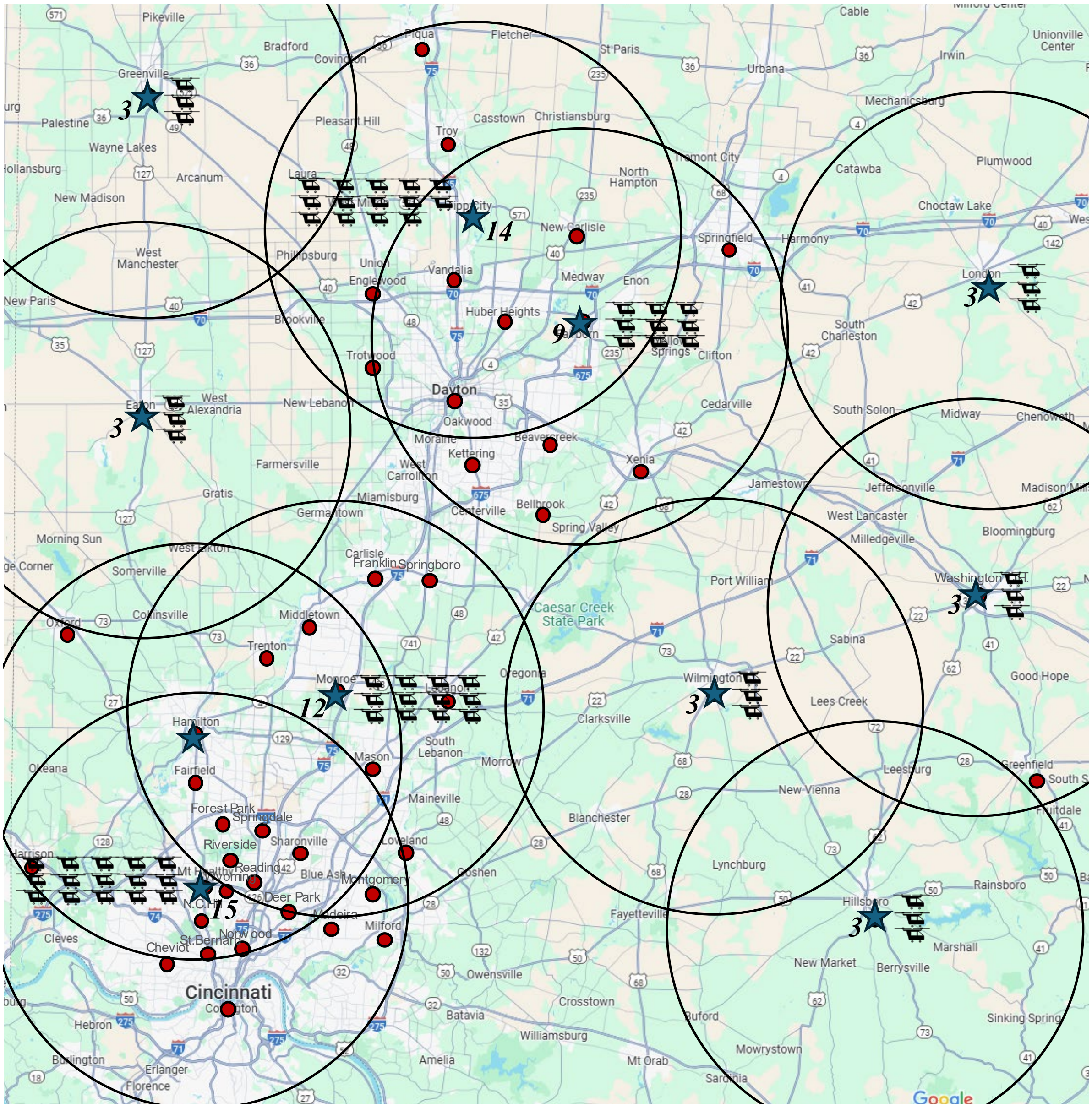

Figure 2. Optimal vertiport locations for $\boldsymbol{r = 15}$ miles and $\boldsymbol{\alpha = 2}$%. The red disks represent city centers and stars represent located vertiports.

Overall, the results indicate a trade-off between accessibility and centralization. Shorter ranges require more evenly distributed infrastructure, ensuring that multiple cities have direct access to air taxi services. In contrast, longer ranges allow the network to consolidate operations in fewer cities, reducing the number of required vertiports but potentially increasing travel distances for passengers. The choice of operational strategy depends on factors such as expected demand, cost efficiency, and service coverage requirements.

Our numerical results highlight the relationship between demand, operational range, and infrastructure costs in the design of UAM networks. As can be observed, increasing demand results in higher costs, primarily driven by the need for more air taxis and, in some cases, additional vertiports. This emphasizes the importance of carefully assessing demand levels to avoid over- or under-investment in infrastructure. Additionally, the operational range plays a critical role in balancing costs and coverage. As expected, longer ranges reduce the need for additional vertiports, yet they require more effective scheduling and management to handle increased air traffic at fewer locations. The distribution of air taxis across cities also reveals the impact of both population size and strategic network planning. Larger cities tend to be prioritized, but smaller or mid-sized cities can also play a key role, particularly when located at strategic points within the network.

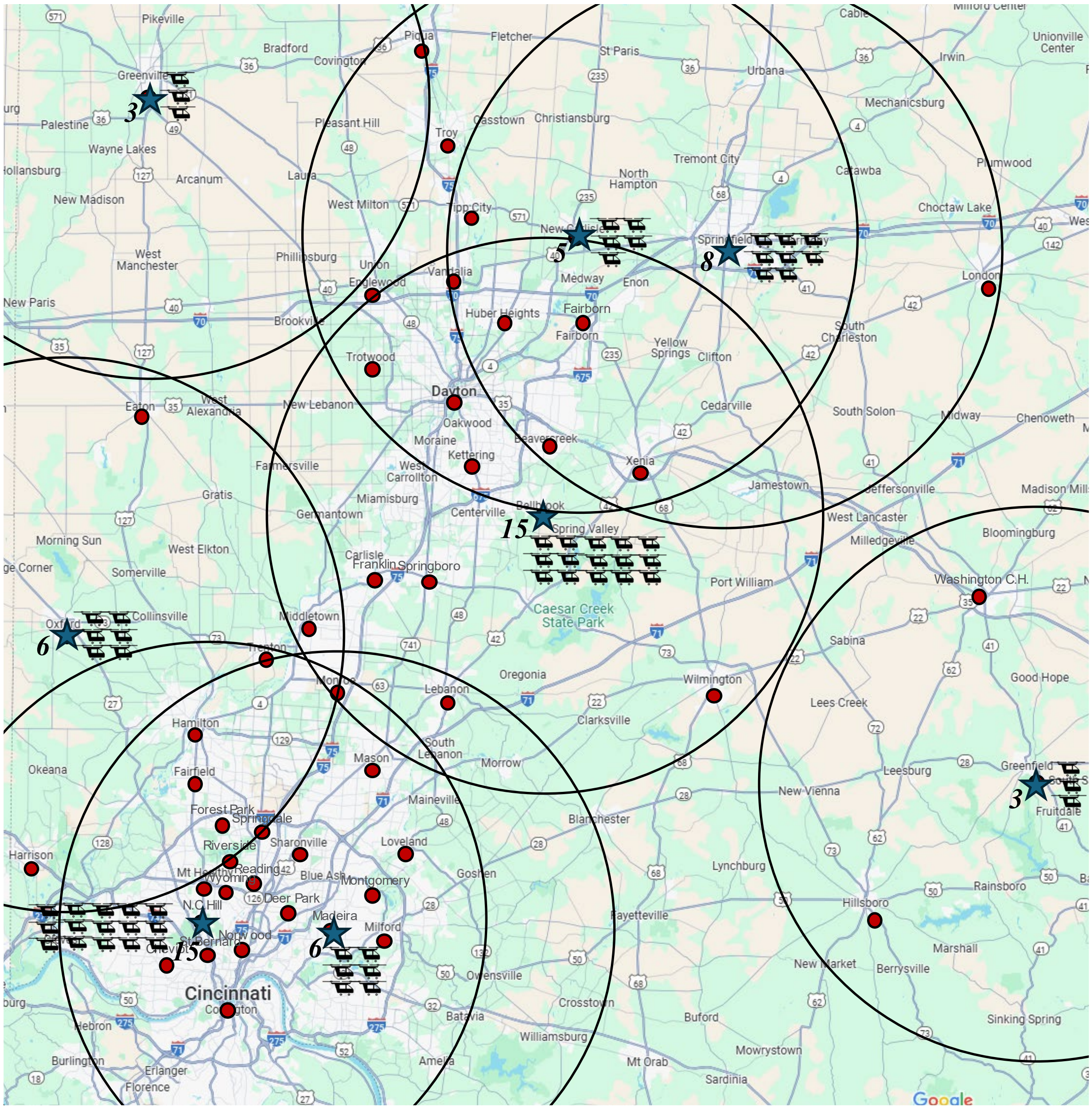

Figure 3. Optimal vertiport locations for $\boldsymbol{r = 20}$ miles and $\boldsymbol{\alpha = 2}$%. The red disks represent city centers and stars represent located vertiports.

5. Conclusion

Set cover models in set theory, are fundamental tools in operations research and in location science. In particular, these approaches aim to identify the minimum subset of locations (facilities) that collectively cover all points of demand within a system. These models have been widely applied in various fields, from emergency response planning (e.g., fire station and ambulance depot locations) to healthcare services, public transportation, telecommunications, and logistics. By minimizing the number of facilities needed to cover all demand points, set cover models provide a cost-effective and efficient solution, especially in scenarios with limited resources and a need for equitable service in an area of interest. In the context of UAM, set cover models are ideal for determining optimal vertiport locations, ensuring that every point within a service area (e.g., metropolitan areas or counties) is covered by at least one vertiport.

When integrated with additional constraints such as demand, fleet size, and capacity, the set cover model offers a scalable and practical approach to infrastructure planning for UAM systems.

Despite the significant advancements in vertiport location and fleet optimization, several challenges remain in designing efficient and scalable UAM networks. Many existing studies focus primarily on strategic facility location or fleet management, with limited integration of dynamic, real-time constraints such as weather conditions, congestion, and shifting demand patterns. Future research can focus on hybrid models that combine data-driven forecasting, adaptive scheduling, and machine learning-based optimization to improve the robustness and adaptability of UAM systems. Additionally, sustainability concerns, regulatory constraints, and infrastructure compatibility must be examined to ensure the long-term viability of air taxi services. Another important future work direction is developing heuristics to efficiently solve large-scale problems, as solving these optimization models using exact methods becomes computationally expensive for larger networks. Finally, stochastic models that account for demand uncertainty can be explored to better capture real-world variability and enhance the robustness of UAM planning under unpredictable conditions.

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Biographies

Zahra Zare holds a bachelor's and master's degree in Industrial Engineering and is pursuing a Ph.D. in Industrial and Human Factors Engineering from Wright State University. She is also pursuing a master's degree in Marketing Analytics and Insights at Wright State University. She possesses over 10 years of marketing and data analysis experience in the industry. Her research interests include optimization modeling, supply chain analytics, and data-driven decision-making. She has published and co-authored several papers on topics ranging from outsourcing reliability to project scheduling, and her current work includes integrated optimization approaches to urban air mobility systems.

Mumtaz Karatas holds a BSc in Industrial Engineering from the Turkish Naval Academy and an MSc in Industrial & Operations Engineering from the University of Michigan. He has six years of experience as an operations research analyst for the navy and obtained his PhD in Industrial Engineering from Kocaeli University. Following his time as a researcher at the Naval Postgraduate School for two years, he served as a faculty member at the Turkish Naval Academy for 10 years.

His primary research focuses on the application of operations research techniques, optimization, machine learning, and data analytics to tackle supply chain design and logistics problems, as well as defense planning problems. He specializes in areas such as facility location and sizing, vehicle/inventory routing, sensor network design, and transportation planning. His recent research includes robust optimization in the context of disaster planning, healthcare resource management, and UAV mission planning.

Yu-jun Zheng (M'06) received the Ph.D. degree from the Institute of Software, Chinese Academy of Sciences, in 2010. He is currently a full-time Professor and the Ph.D. Advisor with Hangzhou Normal University. He has published over 60 scientific papers in journals, including the IEEE Transactions on Evolutionary Computation, the IEEE Transactions on Fuzzy Systems, and the IEEE Transactions on Intelligent Transportation Systems. His research interests include nature-inspired computation and its applications. He is a member of the ACM. He received the 2014 IFORS Prize for the development (runner-up) due to his work on intelligent scheduling of emergency engineering rescue in China.