EXPLORING RIDESHARING IN PASSENGER URBAN AIR MOBILITY: A COMPARATIVE ANALYSIS

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Abstract

There is growing interest in urban air mobility (UAM) as an alternative for passenger and cargo transport around metropolitan areas in a multimodal transportation system that leverages small, electric aircraft. Ridesharing has been proposed as a means of making UAM passenger trips more affordable and environmentally friendly. We present a UAM ridesharing model integrated into an existing computational framework for analyzing daily work commute trips within a metropolitan area. We leverage this model to estimate the potential demand for ridesharing-enabled UAM trips within six metropolitan areas across the United States: Chicago, IL; Cleveland, OH; Dallas, TX; Denver, CO; New York City, NY; and Orlando, FL. We compare results for each metropolitan area with and without ridesharing. Results indicate that ridesharing enables at least an order of magnitude more UAM-preferring passengers than without ridesharing, though specifics vary across metropolitan areas and network sizes. Enabling ridesharing in UAM also considerably lowers the mean and mode value of time for passengers that select the UAM mode, indicating that ridesharing can help make UAM more economically accessible to a larger set of the population. An important caveat is that the UAM ridesharing model does not account for operational constraints, such as aerodrome capacity and aircraft availability, and relies on a perfect knowledge of passenger movements and mode preferences. This leads to high UAM ridesharing volumes that are unlikely to reflect real-world UAM operations and thus serves as an upper bound estimate.

Keywords: advanced air mobility, urban air mobility, ridesharing, operational limits, networks

1. Introduction

Over the past decade, the maturing of various aviation technologies, such as electric propulsion and high degrees of automation, along with the emergence of new business models, such as mobile application-based ridesharing, have coalesced into new operational concepts known collectively as advanced air mobility (AAM). AAM pursues safe, sustainable, affordable, and economically accessible aviation for transformational local and intra-regional missions [1]. Many view AAM missions as ranging from package delivery with small drones to point-to-point, passenger-carrying and cargo flights with novel aircraft across hundreds of miles.

Our paper addresses a subset of AAM known as Urban Air Mobility (UAM), a concept to transport passengers around metropolitan areas. Spurred in part by the Uber Elevate White Paper [2], UAM emphasizes passenger-carrying missions in novel electric vertical takeoff and landing (eVTOL) aircraft that can augment existing metropolitan transportation networks. Determining when and where UAM service is superior to existing modes is a key question, particularly in cities that experience heavy road congestion. The concept of ridesharing, wherein multiple passengers are present on a single aircraft operating on any given UAM trip segment, presents a way to increase the affordability of UAM services. Ridesharing in the ground-based mode (e.g., carpooling) has been shown to reduce the cost burden on travelers [3]. We explore the UAM ridesharing concept in this paper by analyzing potential demand for daily work commute trips within multiple metropolitan areas in the United States both with and without ridesharing.

We seek to better understand the potential for UAM-based ridesharing by building upon the foundation of several years of research examining UAM operational limits. Operational limits describe factors that may inhibit the realization and deployment of large-scale UAM operations. In prior work, we developed a computational analysis framework to model the impact of various identified UAM operational limits [4] and to estimate the proportion of regular work commute trips within a metropolitan (metro) area that may utilize UAM [5, 6]. This paper seeks to consider ridesharing and its impacts on potential UAM demand within metro areas, which was not explicitly explored in previous research. We implement a newly developed UAM ridesharing model that extends the computational framework to address the following research questions:

1. *How does ridesharing impact the number of trips with a UAM segment in a metropolitan area?*
2. *How are economic-based UAM operational limits affected by the addition of ridesharing?*

The remainder of this paper is organized as follows. We first provide an overview of some preceding work in Section 2. A discussion of the methods we use to analyze the various metropolitan areas, including the computational framework and our ridesharing model, is provided in Section 3. The following section details and discusses case study findings, including comparisons among metropolitan areas and with results that do not incorporate explicit ridesharing algorithms (Section 4). Finally, conclusions and future work are outlined in Section 5.

2. Background and Previous Research

Since approximately 2018, numerous studies have assessed the market potential for UAM [1, 7] including in particular metropolitan areas, to assess the potential market size in those locations [5, 8, 9]. Spawned by early market studies, such as those sponsored by NASA [10, 11], and industry desires to launch UAM services [2], the research community explored UAM concepts of operations and infrastructure [12, 13, 14, 15, 16].

Wu and Zhang explored a notional UAM network in the Tampa Bay, FL area [16]. Their study emphasizes the need for well-developed ground infrastructure to optimize the location and quantity of aerodromes[1]. They show that integrating this information with a simulated UAM passenger travel demand dataset can create an improved network. Their study was unique because it employed Geographic Information System (GIS) 3D LiDAR data to determine feasible aerodrome locations based on physical (land area) and regulatory requirements. In comparison, we used inbound and outbound trip totals, median income, and population density to determine potential aerodrome locations guided by network bounding conditions (e.g., facility proximity, range limits, facility count, and facility type). Furthermore, Wu and Zhang found that optimized aerodrome reduce travel costs for passengers and provide a significant reduction in time compared to alternate modes. However, similar to findings from our own work, only a small percentage of trips were predicted to switch from ground mode to UAM. Finally, Wu and Zhang conducted sensitivity analysis by varying pricing and the number of aerodromes, similar to our team's efforts to vary aerodrome network sizes and values of time between passengers [6].

[1] Although many use the term 'vertiport' for UAM or AAM takeoff and landing areas, we use 'aerodromes' to provide a more generic term that encompasses all types of takeoff and landing infrastructure, including vertiports, heliports, and airports with traditional runways. Although the term 'airport' is technically generic enough to encompass all locations from which aircraft takeoff and land, it is often used to refer specifically to aerodromes with multiple-thousand-foot-long runways.

Haan et al. [8] estimated the potential UAM market size in 40 cities across the US basing their demand prediction on cell phone data augmented with census data. Their mode choice models were based on stated-preference surveys to estimate commuter demand for UAM services in each combined statistical area (CSA). Similarly, our ongoing operational limits work uses census data for CSAs to model passenger demand.

A study conducted by Uber of France (Bennaceur et al.) [17] proposed a framework suitable for implementation by an on-demand air-taxi operator using a mixed-integer linear programming model for passenger pooling and aircraft scheduling. Their study proposed creating different classes of service akin to Uber's current ride-hailing model, where a rider would experience shorter wait times for a higher fare, in addition to a standard fare. They argue that this may make the service more affordable and economically accessible. A fundamental difference between the Bennaceur et al. study and our current study is that the Bennaceur et al. study only considers travelers who have explicitly chosen to take an air taxi, whereas our current study analyzes all commute trips in a pre-defined set and assigns each of them a mode preference based on passenger-specific effective cost metric, which combines the vehicle operating cost shouldered by a traveler with a cost associated with the duration of travel for that traveler. Our effective cost metric is described in Section 3.1.2.

The impact of ridesharing coupled with an assumed associated increase in waiting time due to ridesharing was considered by Maheshwari et al. (2020) in [4]. Their ridesharing analysis assesses up to three passengers traveling from and to the same locations, investigating changes in a passenger's travel time and operating cost as more passengers are added to an aircraft for ridesharing. Their study adhered to the assumption that aircraft operating costs are split equally among passengers. In addition, their study further introduced a ridesharing penalty time to account for the waiting period for passengers to arrive. In this case, a passenger flying alone does not see a ridesharing penalty, whereas two-passenger UAM trips will see an arbitrarily chosen ridesharing penalty value of 10 minutes added to both passengers. An additional passenger would then incur an additional 10-minute ridesharing penalty applied to all passengers. Their study found that, given these assumptions, a UAM service would be increasingly less expensive for individual travelers when more travelers are added to a UAM flight. However, as even more passengers are added, their study found that the benefits of cost reduction per passenger brought about by ridesharing begins to diminish, as passengers now have to wait longer due to the additional ridesharing penalty.

The current ridesharing study presented in this paper builds upon the Maheshwari et al. (2020) study, adding fidelity by implementing UAM ridesharing analyses across all daily commuter trips within a metropolitan area (instead of a single route), incorporating an algorithm that pools passengers together based on their individual arrival time at their departure aerodromes and their calculated maximum wait times (such pooling algorithms were not considered in their study).

A 2021 study by Maheshwari & DeLaurentis [18] developed and utilized a Markov decision process framework for ridesharing in on-demand air service operations, focusing on a small subset of trips. The algorithm facilitated ridesharing operations of up to two passengers per aircraft in keeping the computational cost to a minimum. However, the objectives of the Maheshwari & DeLaurentis study are different than that of the current ridesharing study. Specifically, the Maheshwari & DeLaurentis study put forth a passenger-pooling algorithm tailored to on-demand, real-time operations in which air services operate without a pre-defined schedule and are instead initiated based on real-time requests from passengers. This means that the algorithm must respond promptly to these requests, dynamically allocating aircraft resources to fulfill them as quickly as possible. Their study demonstrates that their passenger-pooling algorithm improves over time in its ability to perform fleet distribution and trip scheduling decision-making through reinforcement learning techniques. In contrast, the current ridesharing study is focused on *a priori* analysis on a pre-defined set of commuter trips to determine operational limits and provide insight into the magnitude of potential UAM demand and market share (or mode share) both with and without ridesharing.

3. Methodology

We have developed a standalone ridesharing model termed the Passenger Aggregated Network with Very Efficient Listing (PANVEL). PANVEL analyzes a pre-defined set of commuter trips within a metropolitan area, models wait times for passengers, and is integrated with the pre-existing computational framework to demonstrate the potential for UAM ridesharing in impacting UAM demand across different aerodrome networks in various metropolitan areas [4, 5, 6]. This section describes the ridesharing methodology, and Ref. [19] outlines the UAM ridesharing model in further detail.

An overview of the complete analysis process is shown in Fig. 1, and various elements of the analysis are described in the subsections below.

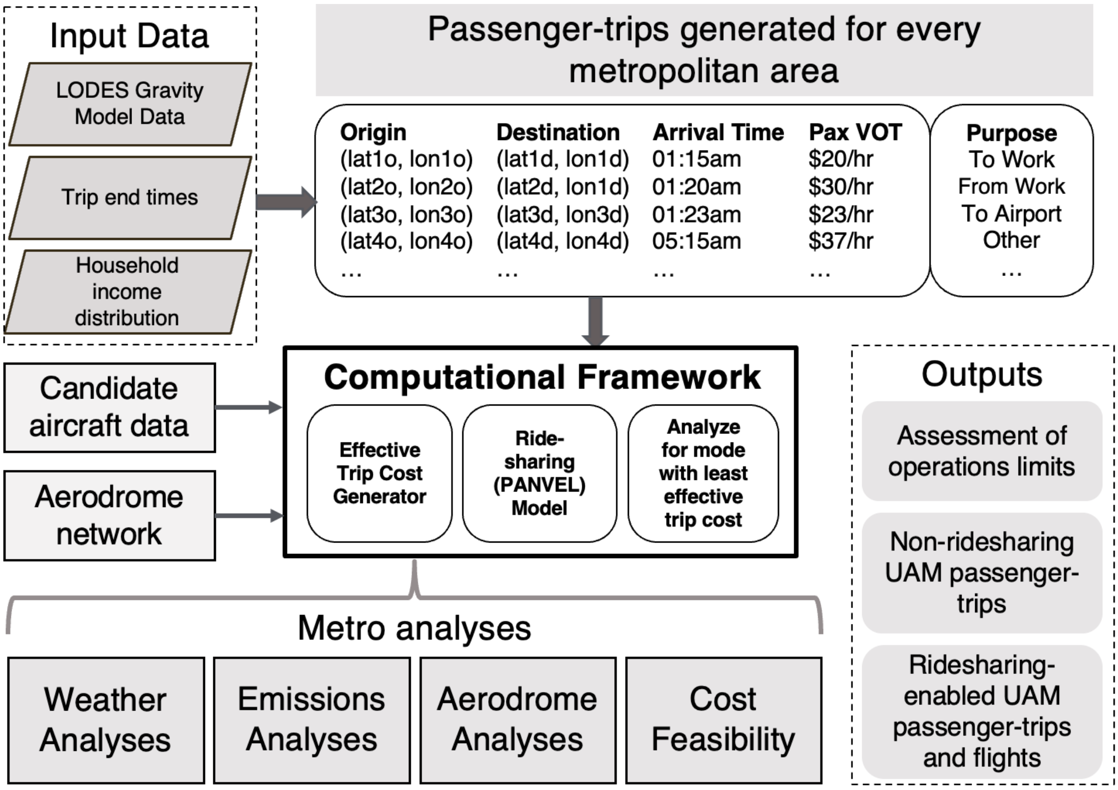


Figure 1 – Overview of the complete analysis process for AAM operational limits, including an enhanced computational framework with the PANVEL ridesharing model for analyzing trips within metropolitan areas, plus additional analysis modules

3.1 Key Components in our Research on UAM Operational Limits

3.1.1 Computational Framework for Analyzing Commuter Trips

Over the past few years, in our research efforts to study UAM operational limits, we developed a computational framework that models commuter trips for a representative day within metropolitan areas of interest. The inputs of the computational framework include an aerodrome network dataset, a commuter trip demand dataset, and a list of parameters that define the notional UAM eVTOL aircraft used in our modeling, described below.

There are three different aerodrome network datasets for each metropolitan area analyzed in this study, each corresponding to a different network size. Varying the size of the aerodrome network for each metropolitan area allows us to model possible future UAM states and operations given uncertainty around constraints in infrastructure and airspace. The largest aerodrome dataset contains the *full* aerodrome network, which in prior publications was referred to as the ‘Large’ aerodrome network [4], and represents all public-use infrastructure that was operational in 2021 as obtained from the FAA National Flight Data Center database [20]. The full aerodrome networks include infrastructure located within the boundaries of the CSA corresponding to each metropolitan area under study plus a 20 kilometer (12.4 mile) buffer zone beyond the boundary. The metropolitan areas of interest are Chicago, Cleveland, Dallas, Denver, Orlando, and New York City.

The remaining aerodrome network datasets describe the ten-aerodrome and three-aerodrome networks, which prior publications have referred to as the 'Medium' and 'Small' aerodrome networks, respectively. The approach used to determine these three- and ten-aerodrome networks were informed in part by engineering judgement and a siting algorithm described in [12]. As described in [6], the three-aerodrome network consists of aerodromes hypothetically placed at a major commercial airport within that metropolitan area, a community location close to a major residential area, and a downtown location close to the city center. Similarly, the ten-aerodrome network consists of aerodromes deemed to be best placed for UAM operations by drawing upon engineering judgment; insights from modeling operations in the three-aerodrome network; and other operational characteristics, including population density, income levels, and distance from city center areas. Because specific siting criteria were considered in the three- and ten-aerodrome networks, these aerodrome networks contain private-use aerodromes in addition to public-use facilities for the Dallas, Denver, New York City, and Orlando metropolitan areas, distinguishing them from the full aerodrome network that includes only public-use aerodromes.

Next, the commuter trip dataset is compiled using the Longitudinal employer-household dynamics Origin-Destination Employment Statistics (LODES) data available from the national census [21], and this data is supplemented with equivalent metro-specific surveys for Chicago. We then perform a UAM trip generation process to identify trips for passengers that entail driving to the nearest aerodrome, flying in a UAM aircraft, and then driving to the final destination. To identify the arrival times for each trip, we sampled data from the National Household Travel Survey (NHTS) [22]. An individual's value of time (VoT) is derived from that individual's income, which is obtained from the American Community Survey (ACS) [23]. The VoT is a critical metric in this study as it determines how much an individual is willing to spend for the time-saving convenience promised by UAM.

The operating cost of the UAM aircraft is assumed to be divided evenly among the passengers onboard for any particular segment. In keeping with assumptions and experiment choices utilized in previous studies, the operating cost rate of the aircraft is assumed to be $605/hr based on estimates from Uber Elevate [24, 25, 4]. The car operating cost rate is based on the Internal Revenue Service's standard 2019 mileage rate of $0.58/mile [26]. The notional aircraft is further assumed to have a range of 92.6 kilometers, or 50 nautical miles, a fixed battery recharging duration of 20 minutes, a taxi-takeoff-climb duration of 3.08 minutes, and a descend-landing-taxi duration of 3.31 minutes. Finally, a 25-minute total UAM mode transition duration is also assumed for passengers taking the UAM mode[2] [25]. It should be noted that this UAM mode transition duration is completely separate from the wait times that are modeled within the ridesharing methodology, described in Section 3.2.

3.1.2 Analyzing Commuter Mode Preferences and UAM Operations Limits

In this computational framework, each commuter is assigned a mode preference based on their estimated *effective trip cost* [27]. This effective trip cost consists of two components—the first of which is the direct travel cost of the passenger that is found by summing the operating costs of all vehicles involved in a given mode of travel. The second component, the *time cost*, is a product of an individual's value of time (VoT) and the duration required to complete that individual's trip.

[2]This transition duration is derived from the assumption that a passenger would spend 15 minutes in the terminal building before they depart on a UAM flight (taking into account the time spent by a passenger checking in, walking through the terminal, undergoing security checks, boarding the aircraft, and safety briefings), plus 10 minutes immediately after UAM flight arrival (taking into account the time taken for a passenger to disembark and reach their last-mile ground transport mode.)

In this study, we consider two transportation mode options for each commuter trip: the car mode and the UAM mode. The car mode involves an individual traveling from their origin to their destination fully by private ground transport. The UAM mode involves three segments, with an initial ground segment between an individual's origin point A and their departure aerodrome, then a UAM segment between their departure and arrival aerodromes, followed by another final 'last-mile' ground segment between their arrival aerodrome and their destination point. These two modes are depicted in Fig. 2. The assignment of mode preferences are determined by an assumption that an individual traveler would choose the mode with the least overall effective trip cost. Trips that have a lower effective cost associated with the UAM mode (as opposed to the car mode) are termed *UAM-preferred trips* [4].

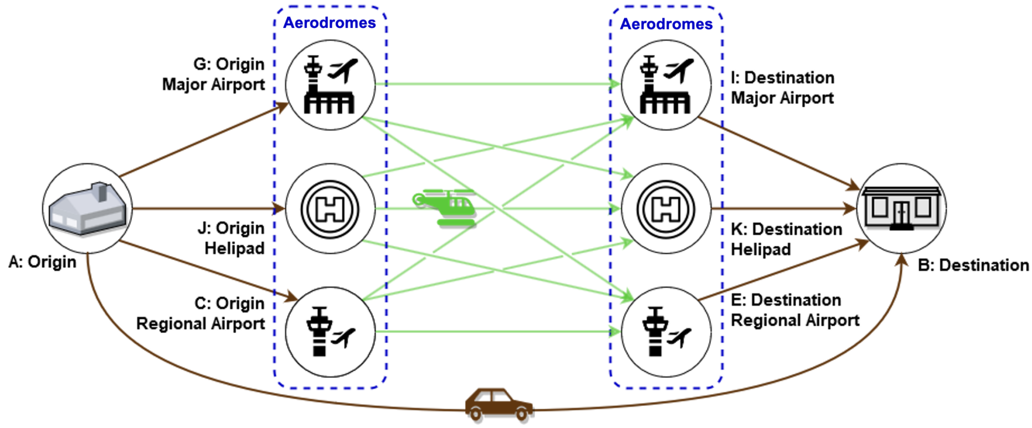


Figure 2 – Network model of commuting mode options within the computational framework: A→B for the car mode and A→C/G/J→E/I/K→B for the UAM mode.

The computational framework computes the distance, duration, carbon dioxide (CO_2) emissions generated, vehicle operating cost, as well as effective cost for each segment in both the UAM mode and the car mode for all commuter trips in a metropolitan area, which form part of the computational framework outputs. After obtaining data for mode preferences and other information for each trip from the computational framework, further analyses can be conducted. Examples of past analyses include estimating the aggregate CO_2 emissions caused by UAM operations [28] and evaluating constraints imposed on UAM operations due to adverse weather [29]. Another past study demonstrated the operational limits on capacity and throughput at aerodromes based on gate availability, touchdown-liftoff pad or runway availability, aircraft availability, and the initial distribution of aircraft on ground throughout a UAM network [6].

The authors encourage readers to refer to Refs. [30, 25, 4, 31, 5, 6, 12] for a chronological understanding of the development of the computational framework, including the processes for trip and network generation, assigning departure and arrival aerodromes to trips, calculating effective costs, and the selection of existing infrastructure for aerodrome networks.

3.2 Ridesharing Considerations

A previous study by Maheshwari et al. performed parametric sweeps of operating cost to investigate the impact of reducing vehicle operating cost on the number and mode share of UAM-preferred trips for a given metropolitan area [5]. Although these experiments were intended to demonstrate possibilities given lower eVTOL operating costs, they were also used as an approximation for the potential benefits of ridesharing. For example, a 50% operating cost reduction could also be viewed as a UAM ridesharing scenario with two passengers onboard each aircraft, a 67% operating cost reduction could be viewed as a three-passenger UAM ridesharing scenario, and so forth. By dividing the operating cost of the aircraft among the passengers onboard, the operating cost burden on an individual passenger is reduced, which can increase the number of UAM-preferred trips in a particular metro area. However, this simple cost-reduction method does not account for several important characteristics associated with ridesharing, such as longer wait times for passengers and the need to have multiple passengers desiring to travel at the same time between the same locations, which we explore in this paper.

To explore the impacts of ridesharing on traveler mode choice within a metropolitan area, we developed and implemented a ridesharing model we refer to as Passenger Aggregated Network with Very Efficient Listing (PANVEL) [19]. The PANVEL model aims to aggregate passengers traveling between the same origin and destination onto a single UAM flight. It utilizes passenger data such as VoT, mode-dependent effective cost, and trip duration to estimate the number of passengers with effective cost metrics that indicate preference for the UAM mode. This model divides vehicle operating costs evenly among all passengers onboard and seeks to group the highest number of individuals possible for a given UAM flight.

The PANVEL model initializes the passenger order based on arrival times at a given departure aerodrome then re-orders the passenger list by the latest arrival time possible with respect to passengers' combined wait time and arrival time. Each traveler's maximum wait time at the origin aerodrome is calculated by determining the amount of time at which the effective cost of the UAM mode and base mode would be equivalent for the passenger, assuming the aircraft costs are divided among the maximum number of passengers possible on the aircraft, which is taken to be N. The latest departure time for each traveler is then determined from the individual's maximum wait time and arrival time at the aerodrome. The model examines the first N passengers scheduled to arrive at the origin aerodrome with the same destination aerodrome and assesses whether this group of N passengers is suitable for sharing a ride; specifically, if any of the N passengers fail to arrive prior to the latest departure time for all passengers, the current group of N is considered incompatible. Then, the passenger with the lowest maximum wait time is excluded in favor of the next passenger, and the process is repeated until a compatible group is found or the passenger list for that origin-destination pair is exhausted.

Once the passenger list for a given origin-destination pair is exhausted considering N passengers in the aircraft, the model resets and calculates wait times again, this time considering $N-1$ passenger operations in an N-seat aircraft, for all the unallocated passengers who could not be accommodated on ridesharing trips with N passengers. The model again iterates chronologically through the unallocated passenger list, considering their original arrival times at the origin aerodrome. This analysis continues until at least two passengers are being considered. Remaining passengers not allocated to any two-, three-, or four-passenger UAM trips undergo a separate comparison of their effective costs between the car mode and the single-passenger UAM mode, akin to previous studies [4, 5]. Those passengers with a lower UAM mode effective cost are then assigned a single-passenger UAM flight in our modeling.

For the aircraft considered in this work, operations are simulated on four-seater aircraft considering four, three, and two passengers at a time for ridesharing. This method also prioritizes higher load factors based on the rationale that, with sub-optimal load factors, the passengers actually flying would have to pay more to cover the cost of the empty seats. Since the revenue models for such UAM operations are beyond the scope of this paper, it was deemed prudent to maximize load factors. The flowchart in Fig. 3 demonstrates the methodology of the PANVEL ridesharing model.

Though perhaps counterintuitive, our analysis indicates that passengers with a high VoT may be willing to wait longer in the presence of other competitive travel modes. This is due to the high time cost in the ground travel mode that outweighs the increased vehicle operating costs in the UAM mode in the effective cost calculations[3].

[3]The VoT-based exclusion criterion is further discussed in [19]

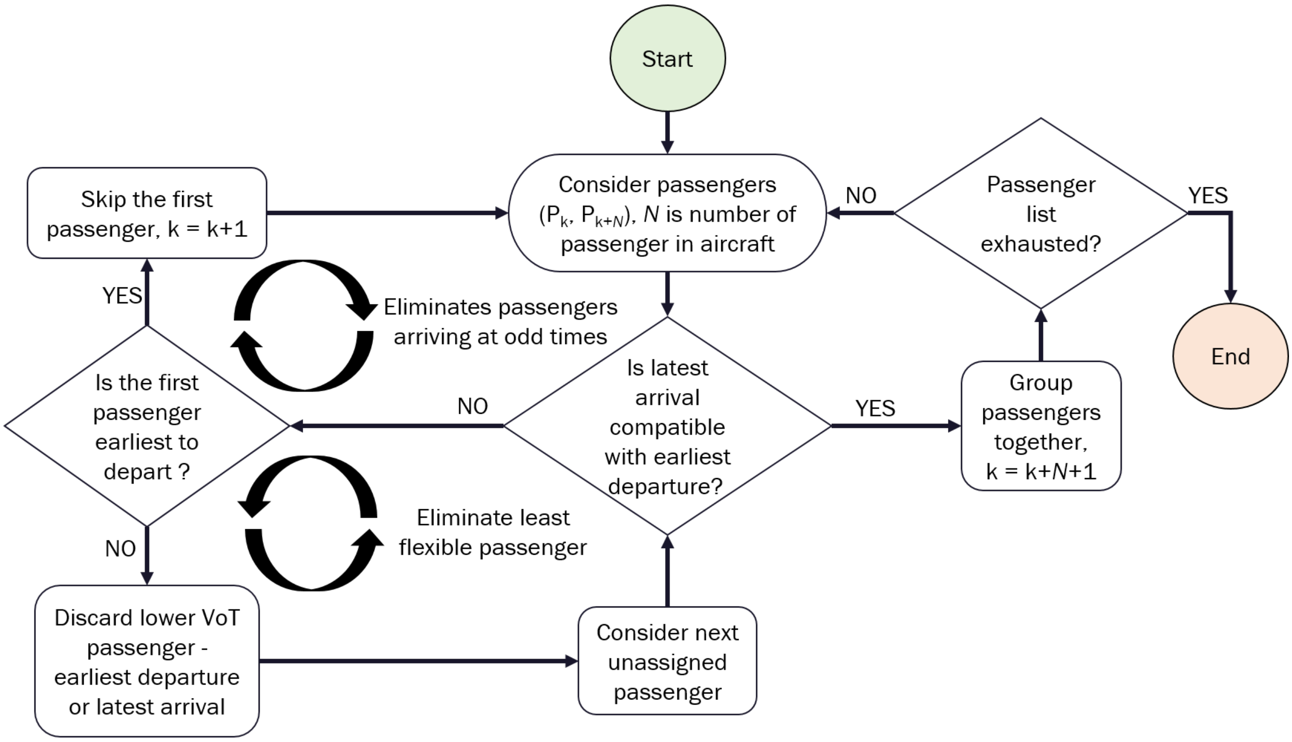


Figure 3 – Operational flow of the PANVEL ridesharing model [19]

In reality, UAM operators and passengers would not possess foresight regarding the arrival times of all passengers; therefore, the PANVEL model represents an idealized case in which a near-maximum number of individuals select the UAM mode. Because of this, different ridesharing models would be required by UAM operators to apply in their operations. We further acknowledge that results from studies leveraging PANVEL are likely to predict much larger improvements brought about by enabling UAM ridesharing than expected in practice. However, our intent is to reasonably estimate a rough upper limit on possible ridesharing-enabled UAM trips to provide insight on the importance of ridesharing on UAM market share.

4. Case Studies

Case studies of ridesharing-enabled UAM operations were performed using the PANVEL-enabled computational framework across six U.S. metropolitan areas (Chicago, Cleveland, Dallas, Denver, New York City, and Orlando) for three different aerodrome networks in each metro area. The subsections below detail the various inputs and other experiment choices used in each study, as well as our findings on ridesharing-enabled UAM operations and the implications of ridesharing on the potential market share of UAM.

Note that the ridesharing figures presented in this paper do not take into account aerodrome throughput and capacity operational constraints caused by the availability of gates, touchdown-liftoff (TLOF) pads and/or runways, and aircraft. Therefore, the UAM operations described below are considered unconstrained (i.e., not constrained by aerodrome throughput operational limits). Research is ongoing to analyze constrained ridesharing-enabled UAM operations across the metropolitan areas, and these are also expected to be presented in future publications.

4.1 Aerodrome Network and Aircraft Parameters

The networks of existing infrastructure (e.g., vertiports, airports, and other facilities) that *may* be utilized for UAM operations, referred to as aerodromes, are the same networks developed in previous research [6, 12]. Diagrams of full aerodrome networks, ten-aerodrome networks, and three-aerodrome networks, as well as CSA bounds for all metropolitan areas, can be found in [6], where the aerodrome networks were referred to as 'Large', 'Medium', and 'Small', respectively.

We continue to utilize the $605/hour operating cost for a notional eVTOL aircraft consistent with prior studies, which is based on an estimate from Uber in their 'Launch' cost scenario [24, 25, 4]. We also assume that the notional aircraft used in this study has a maximum capacity of four passengers. Therefore, the PANVEL ridesharing model used in this study has been optimized for one- to four-passenger (pax) trips. Although the incorporation of the PANVEL ridesharing model allows us to account for ridesharing of up to four passengers, it does not account for ground traffic delays, repositioning, airspace constraints, or re-routing measures. The model has also not considered ridesharing on ground transportation modes, which may reduce the effective cost of performing a trip fully on ground.

4.2 Impacts of UAM Ridesharing on Estimated UAM Demand

We present a summary of non-ridesharing and ridesharing-enabled UAM operations across six metropolitan areas, each comprising three aerodrome network types, in Table 1. Note that for the non-ridesharing scenarios, the estimated number of UAM-preferred passenger-trips will be equivalent to the estimated number of flights, since the sole passenger has the eVTOL aircraft to themselves.

Ridesharing brings a marked increase in the estimated number of unconstrained UAM-preferred passenger-trips (or UAM-preferring passengers) across most metropolitan areas and aerodrome networks, even when the non-ridesharing scenario sees zero UAM-preferred trips, as is the case with the Cleveland metropolitan area. The one exception to this is the Cleveland three-aerodrome network, where no trips were assigned any UAM segments based on the effective cost metric within the computational framework. These results indicate why ridesharing is necessary to enable large-scale UAM operations and reduce operating costs on a per passenger-mile basis.

The breakdown of UAM flight occupancies (between one and four passengers) vary by metro area and network size, but in most cases a majority of flights (above 94%) are four-passenger flights, as four-passenger flights result in the lowest operating costs shouldered per passenger. This also translates into high average load factors for a majority of these networks (above 98%). The lone exception to this is the Dallas three-aerodrome network, with 78.5% of flights being four-passenger flights, and a 93% estimated load factor.

Below, we present and discuss case studies on selected metropolitan areas and network sizes to shed more light on the landscape of ridesharing-enabled UAM operations. We compare the three-aerodrome network and the ten-aerodrome network in selected metropolitan areas to account for future UAM infrastructure states and investigate impacts caused by augmenting the number of aerodromes to be used for UAM services.

4.2.1 Case 1: Chicago full aerodrome network

We assessed 8,627,698 unique passenger-trips within the Chicago metropolitan area, with a full complement of 70 public-use aerodromes available for UAM services. Of these passenger-trips, 2,907 of them are UAM-preferred without ridesharing, flown on 2,907 flights. Enabling ridesharing increases UAM preference to an estimated 154,093 passenger-trips flown on 38,996 flights, for a network-wide load factor of nearly 99% with 96.5% of flights being four-passenger flights. Table 2 shows a breakdown of one- to four-passenger UAM flights for this network.

Table 1 – Summary table of estimated UAM-preferring passenger demand and number of UAM flights for both the non-ridesharing and ridesharing-enabled scenarios, showing increases to varying degrees when ridesharing is enabled across all networks.

Metropolitan Area	**Aerodrome Network Size**	**Non-ridesharing**		**Ridesharing**	
		# UAM-preferred	**% UAM mode share**	**# UAM-preferred**	**% UAM mode share**
Chicago 8,627,698 total pax	3	49 pax 49 flights	0.001%	9,168 pax 2,305 flights	0.106%
	10	815 pax 815 flights	0.009%	92,740 pax 23,263 flights	1.07%
	70 (full)	2,907 pax 2,907 flights	0.034%	154,093 pax 38,996 flights	1.79%
Cleveland 1,987,966 total pax	3	0 pax 0 flights	0%	0 pax 0 flights	0%
	10	0 pax 0 flights	0%	48 pax 12 flights	0.002%
	72 (full)	0 pax 0 flights	0%	214 pax 54 flights	0.011%
Dallas 6,570,232 total pax	3	1 pax 1 flight	<0.001%	346 pax 93 flights	0.005%
	10	41 pax 41 flights	0.001%	8,026 pax 2,021 flights	0.122%
	113 (full)	534 pax 534 flights	0.008%	46,381 pax 11,822 flights	0.706%
Denver 2,504,562 total pax	3	0 pax 0 flights	0%	1,037 pax 261 flights	0.041%
	10	175 pax 175 flights	0.007%	52,709 pax 13,253 flights	2.10%
	27 (full)	1,629 pax 1,629 flights	0.065%	86,474 pax 21,694 flights	3.45%
New York City 17,082,594 total pax	3	146 pax 146 flights	0.001%	15,763 pax 3,966 flights	0.092%
	10	4,071 pax 4,071 flights	0.024%	129,358 pax 32,467 flights	0.757%
	113 (full)	14,136 pax 14,136 flights	0.083%	367,686 pax 92,769 flights	2.15%
Orlando 2,609,774 total pax	3	0 pax 0 flights	0%	138 pax 35 flights	0.005%
	10	9 pax 9 flights	<0.001%	43,117 pax 10,797 flights	1.65%
	49 (full)	278 pax 278 flights	0.011%	192,626 pax 48,330 flights	7.38%

Table 2 – Chicago full aerodrome network UAM ridesharing-enabled operations: a breakdown of one-to four-passenger UAM flights. Of the 8,627,698 total trips modeled in the Chicago metropolitan area, 154,093 are UAM-preferred, while 8,473,605 are car-preferred.

Trip Type	**4-pax**	**3-pax**	**2-pax**	**1-pax**	**UAM Total**	**UAM-preferred (%)**
# Flights	37,643	913	342	98	38,996	–
# Passengers	150,572	2,739	684	98	154,093	1.79%

These UAM-preferring passengers are carried on 754 unidirectional (one-way) aerodrome pairs, or flight routes, between 44 aerodromes within the Chicago full aerodrome network. This leaves 26 aerodromes without UAM-preferring passengers. These flight routes and aerodromes are shown on Fig. 4a, where it can generally be seen that UAM passengers and flights are concentrated closer to the Chicago city center, likely in and around population centers. Fig. 4a also shows that the aerodromes that see no UAM-preferring passenger service at all are among the furthest away from these population centers.

As a point of comparison, Fig. 4b shows the UAM-preferred landscape in the Chicago full aerodrome network when ridesharing is disabled. The 2,907 UAM-preferring passengers in this case are carried on 451 unidirectional aerodrome pairs between 43 aerodromes. In both sub-figures on Fig. 4, all flight routes are represented by line widths that scale with the square root of the total number of UAM passengers in both directions. This scaling was done purely for the purposes of data visualization to reduce the contrast between the highest and lowest total passenger numbers.

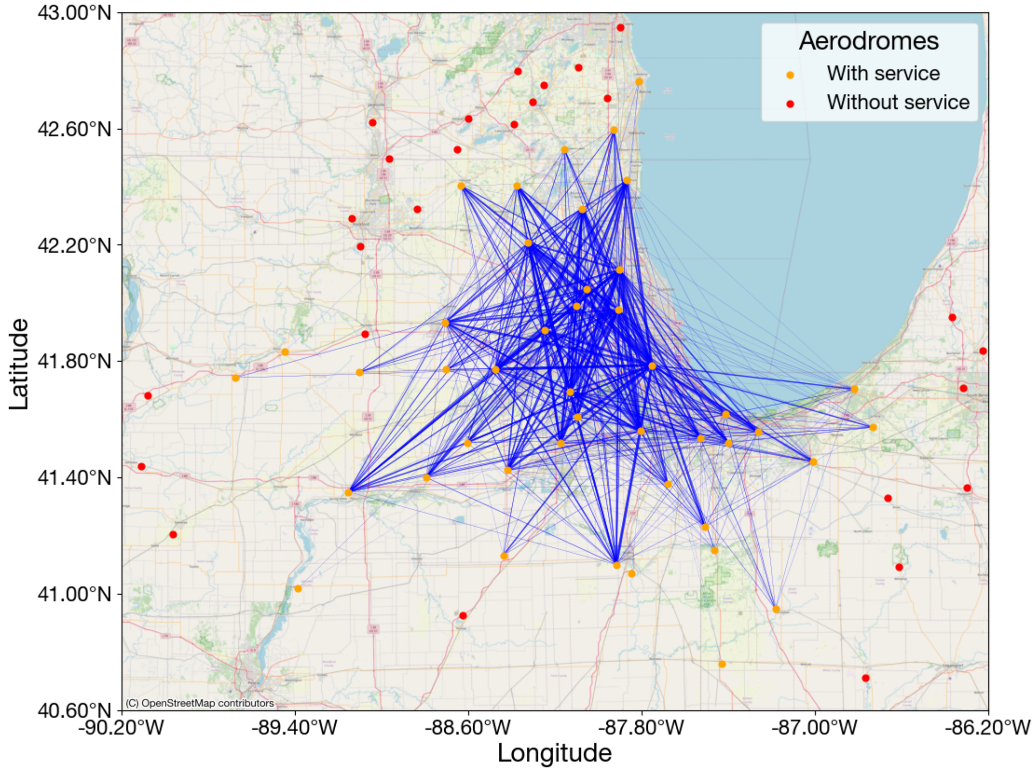
We define *total aircraft movements* within an aerodrome as the sum of aircraft arrivals into and departures out of that aerodrome. A similar definition is applied for *total passenger movements*. The five busiest aerodromes in this network with UAM ridesharing using these measures are outlined in Table 3. Among all aerodromes represented in the Chicago full aerodrome network, we found the busiest aerodrome, Chicago Midway International (MDW), to be closest to the Chicago city center.

Table 3 – Busiest aerodromes by estimated total daily UAM aircraft and passenger movements in the Chicago full aerodrome network with UAM ridesharing.

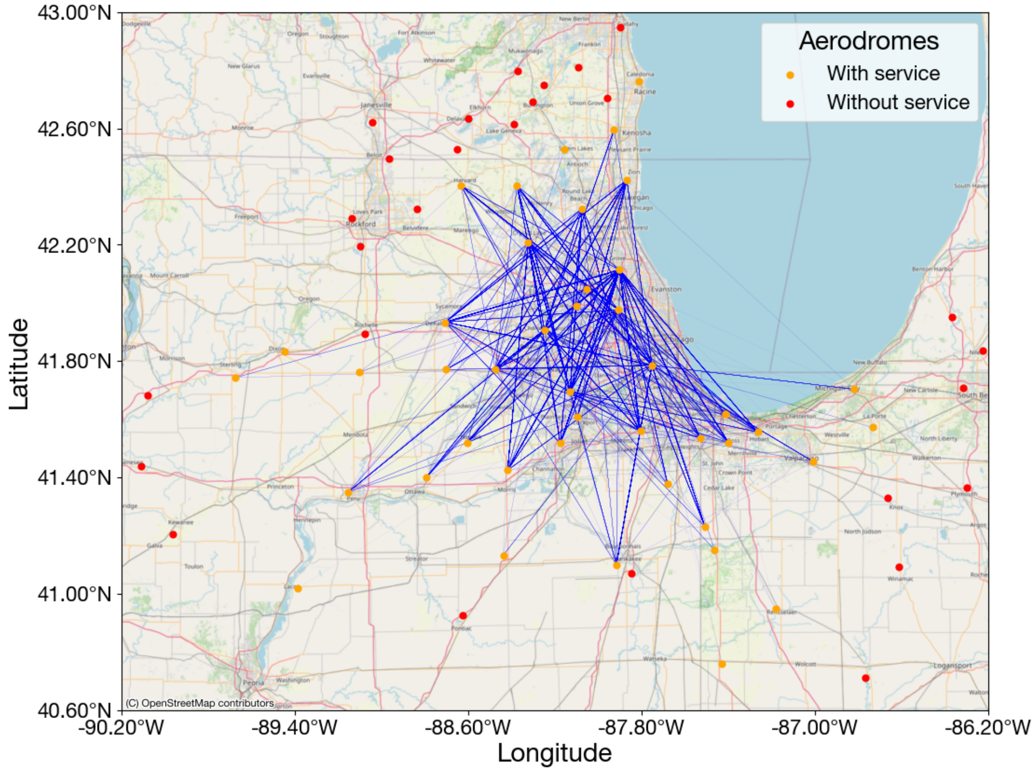
Aerodrome		**Aircraft Movements**	**Passenger Movements**
Chicago Midway	(MDW)	10,307	40,713
Chicago Executive	(PWK)	7,368	29,331
Lake in the Hills	(3CK)	5,612	22,252
Bolingbrook's Clow	(1C5)	5,131	20,320
Tinley Park Helistop	(TF8)	4,835	19,232

Four of these aerodromes constitute the two busiest bidirectional aerodrome pairs:

1. Lake in the Hills (3CK) $\Leftrightarrow$ Chicago Midway (MDW)
   - 66.4 km (35.9 nmi) straight-line distance
   - 47.3 minutes UAM segment duration
   - 3CK–MDW: 3,084 passengers on 772 flights
   - MDW–3CK: 3,037 passengers on 791 flights
2. Chicago Executive (PWK) $\Leftrightarrow$ Tinley Park (TF8)
   - 62.2 km (33.6 nmi) straight-line distance
   - 46.2 minutes UAM segment duration
   - PWK–TF8: 2,108 passengers on 527 flights
   - TF8–PWK: 2,100 passengers on 525 flights



(a) Ridesharing-enabled UAM operations in the Chicago full 70-aerodrome network. 44 aerodromes see UAM-preferring passenger service carrying 154,093 passengers.



(b) Non-ridesharing UAM operations in the Chicago full 70-aerodrome network. 43 aerodromes see UAM-preferring passenger service carrying 2,907 passengers.

Figure 4 – A comparison of UAM operations in the Chicago metropolitan area under the full aerodrome network with and without ridesharing. Aerodromes with passenger service are denoted by orange circles. Remaining aerodromes are denoted by red circles. Blue lines represent flight routes; line widths vary based on the total number of passengers in both directions. Background map data © OpenStreetMap contributors. Data available under the Open Database License [32]

Of particular interest, all flights between PWK and TF8 are four-passenger flights. Note that the UAM segment durations listed here include a 25-minute UAM mode transition duration assumed for all UAM passengers. Shown in Fig. 5 are the five busiest aerodromes and the two busiest bidirectional aerodrome pairs for UAM ridesharing operations in the Chicago full aerodrome network.

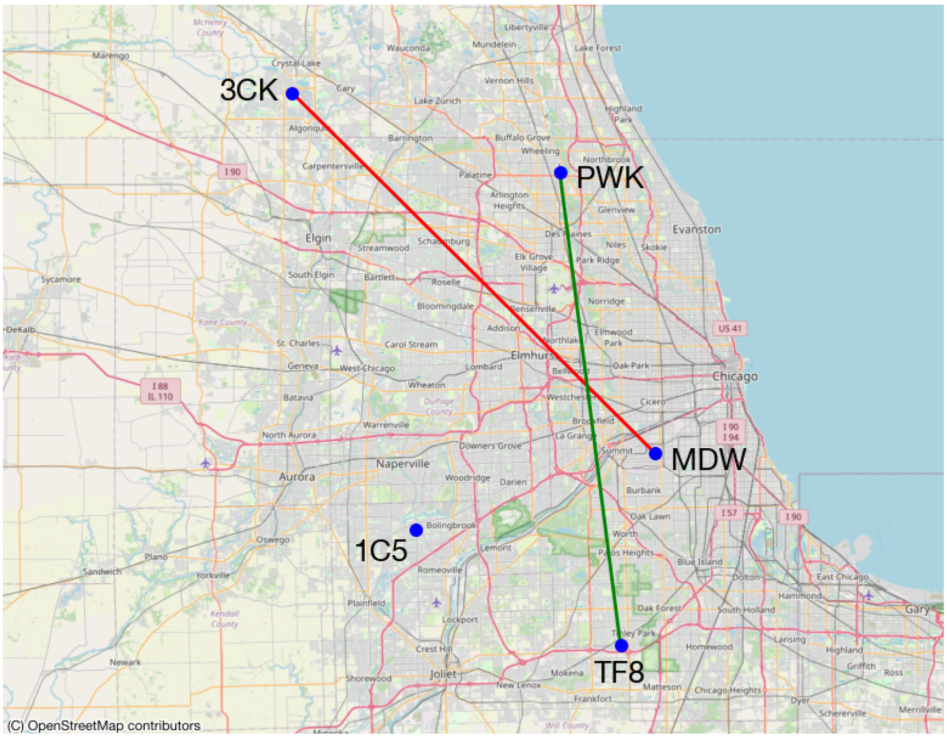


Figure 5 – Busiest aerodromes and aerodrome pairs for UAM ridesharing operations in the Chicago full aerodrome network.
Background map data © OpenStreetMap contributors. Data available under the Open Database License [32]

4.2.2 Case 2: Chicago three-aerodrome and ten-aerodrome networks

The same 8,627,698 unique passenger-trips within the Chicago metropolitan area were analyzed with a three-aerodrome and ten-aerodrome network to estimate the impact of UAM infrastructure levels. These networks include private-use aerodromes whose locations were estimated to be best-suited for UAM operations [6, 12]. This case study will focus on comparing these two networks.

Without UAM ridesharing, we estimate only 915 UAM-preferred passenger-trips and flights on the Chicago ten-aerodrome network. These figures increase to 92,739 passengers on 23,262 flights when ridesharing in UAM operations is enabled. Here, 98.9% of flights are four-passenger flights, with an estimated network-wide load factor of 99.7%. Table 4 shows a breakdown of these ridesharing-enabled UAM-preferring passengers and flights.

Table 4 – Chicago ten-aerodrome network UAM ridesharing-enabled operations: a breakdown of one- to four-passenger UAM flights. Of the 8,627,698 total trips modeled in the Chicago metropolitan area, 92,740 are UAM-preferred, while 8,534,959 are car-preferred.

Trip Type	4-pax	3-pax	2-pax	1-pax	UAM Total	UAM-preferred (%)
# Flights	23,007	201	54	1	23,263	–
# Passengers	92,028	603	108	1	92,740	1.07%

Reducing the aerodrome network size to three yields an estimated 49 UAM-preferring passengers when ridesharing is disabled. Enabling ridesharing results in an estimated 9,168 UAM-preferring passengers flown on 2,305 flights. Similar to the ten-aerodrome network, 98.2% of all flights are four-passenger flights, with an estimated network-wide load factor of 99.4%. Table 5 shows a breakdown of these ridesharing-enabled UAM-preferring passengers and flights.

Table 5 – Chicago three-aerodrome network UAM ridesharing-enabled operations: a breakdown of one- to four-passenger UAM flights. Of the 8,627,698 total trips modeled in the Chicago metropolitan area, 9,168 are UAM-preferred, while 8,618,530 are car-preferred.

Trip Type	**4-pax**	**3-pax**	**2-pax**	**1-pax**	**UAM Total**	**UAM-preferred (%)**
# Flights	2,264	30	11	0	2,305	–
# Passengers	9,056	90	22	0	9,168	0.106%

In the Chicago ten-aerodrome network, the John H. Stroger Hospital of Cook County Heliport (IL75) emerged as the aerodrome with the highest number of UAM-preferring passengers and UAM flights, with the aerodrome seeing an estimated 10,023 unconstrained daily UAM aircraft movements carrying 39,952 passengers. On the other hand, the IL75 aerodrome was found to be the second busiest in the Chicago three-aerodrome network with 2,114 unconstrained UAM aircraft movements carrying 8,404 passengers. Note that IL75 is considered a Chicago city center/'downtown' location in this study.

The busiest aerodrome in the Chicago three-aerodrome network is the DuPage Airport (DPA), with an estimated 2,300 unconstrained aircraft movements, in total carrying 9,150 passengers. On the other hand, of the aerodromes in the Chicago ten-aerodrome network, DPA was found to be the fifth busiest with 5,571 aircraft movements and 22,201 passenger movements. This reflects how changing the aerodrome network size and topography can greatly influence demand for UAM services in various aerodromes, particularly when an aerodrome is made available that reduces circuitous travel routings for passengers.

4.2.3 Case 3: Denver ten-aerodrome network

This case study examines the 2,504,562 passenger-trips modeled in the Denver metropolitan area, generating UAM-preferred trips with and without ridesharing. The Denver ten-aerodrome network contains seven private-use aerodromes (mostly helipads adjacent to, or on top of, hospital buildings) plus three public-use aerodromes. A non-ridesharing UAM scenario yields 175 UAM-preferring passengers on 26 flight routes between all ten aerodromes. In contrast, a ridesharing-enabled UAM scenario yielded an estimated 52,709 passengers on 13,253 flights, covering 65 flight routes between all ten aerodromes in the network. The Denver ten-aerodrome network demonstrates a load factor of just over 99.4%, with 98.3% of flights being four-passenger flights. Table 6 provides a breakdown of these ridesharing-enabled UAM flights. Table 7 outlines the five busiest aerodromes by unconstrained total aircraft movements within the Denver ten-aerodrome network.

Table 6 – Denver ten-aerodrome network UAM ridesharing-enabled operations: a breakdown of one-to four-passenger UAM flights. Of the 2,504,562 total trips modeled in the Denver metropolitan area, 52,709 are UAM-preferred, while 2,451,853 are car-preferred.

Trip Type	**4-pax**	**3-pax**	**2-pax**	**1-pax**	**UAM Total**	**UAM-preferred (%)**
# Flights	13,030	144	78	1	13,253	–
# Passengers	52,120	432	156	1	52,709	2.10%

Table 7 – Busiest aerodromes by estimated total daily UAM aircraft and passenger movements in the Denver ten-aerodrome network with UAM ridesharing.

Aerodrome		Aircraft Movements	Passenger Movements
Denver Health HP	(CO35)	6,717	26,736
N Colorado Medical Ctr HP	(98CO)	5,220	20,849
Skylane Ranch AP	(17CO)	3,543	14,163
Parker Adventist Hospital HP	(CD31)	3,281	13,025
Rocky Mountain Metro AP	(BJC)	2,748	10,904

The unconstrained nature of the modeling is apparent from the results in Table 7. The current results for the Denver ten-aerodrome network estimate tens of thousands of passengers on thousands of flights from hospital helipads, which are not designed for such large volumes of passenger and aircraft movements. We take the Denver Health Heliport (CO35) as an example, shown in Table 7 as the aerodrome with the largest estimated number of aircraft and passenger movements in an unconstrained scenario. The CO35 aerodrome contains a total of two touchdown-liftoff (TLOF) pads [33], with no additional taxiways or gates. We assume that these TLOF pads are the points of aircraft embarkation and disembarkation for passengers. Furthermore, we determined that these TLOF pads are too close together to allow for simultaneous operations from both pads [34].

In our modeling, we found that the 07:00 (7 AM) hour is the busiest for the CO35 aerodrome, with 3,845 passengers arriving at the aerodrome on 962 flights; and 183 passengers departing the aerodrome on 46 flights. Figure 6 shows the hourly distribution of unconstrained aircraft movements at the CO35 aerodrome. Even assuming an aggressive three-minute inter-arrival time for each TLOF pad, which leaves approximately 2 to 2.5 minutes for aircraft turnaround, the CO35 aerodrome will only be able to handle just under 40 flight arrivals and 40 flight departures per hour. This is significantly lower than the 962 arriving flights required to fulfill all UAM-preferred trip demand into the CO35 aerodrome for that hour and demonstrates that aerodrome topology and throughput can place significant constraints on real-world UAM operations. It is worth noting that these large volumes of passenger and aircraft movements may point to a need for a purpose-built aerodrome to handle such capacity.

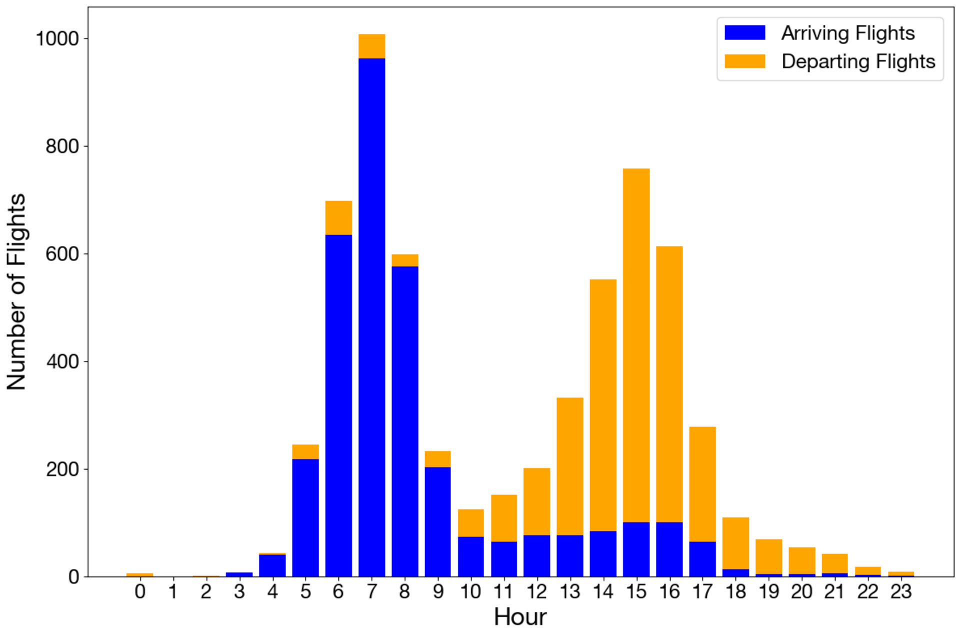


Figure 6 – Hourly distribution of unconstrained aircraft movements departing from and arriving at the Denver Health Heliport (CO35) aerodrome in the Denver ten-aerodrome network, showing that aircraft movements peak at hour 7 (corresponding to 07:00 or 7 AM) in our modeling

In the computational framework, each passenger-trip was assigned a departure and arrival aerodrome for the UAM mode. The *UAM mode share* represents the percentage of UAM-preferring passengers for a specific aerodrome pair among all passenger-trips assigned to that pair. Fig. 7 plots the UAM mode share of every aerodrome pair (or flight route) in the Denver ten-aerodrome network as a function of their distance. Each of the 65 aerodrome pairs are represented by blue circles. A positive correlation suggests a roughly linear relationship between the UAM mode share and the flight distance; however, there is a fairly wide dispersion in the data, especially among routes with distances between 55 and 65 km. Several factors likely contribute to this dispersion, including the road network and VoT of individuals living or working near the aerodromes in these pairs. The increased UAM mode share, which results from increased time and effective cost savings, on longer UAM segments compared to shorter flight distances is particularly notable for flights greater than just over 60 km. This increased mode share is likely due to the 25-minute UAM mode transition time modeled in the computational framework, which reduces the relative time and effective cost savings of shorter UAM trips compared to longer trips.

Figure 8 shows the UAM mode share of all 65 aerodrome pairs in the Denver ten-aerodrome network as a function of the UAM segment duration that corresponds to those aerodrome pairs. This UAM segment duration includes the 25-minute UAM mode transition duration, giving a minimum overall segment duration of approximately 38 minutes. There is a gap approximately between the 55-minute mark and the 80-minute mark due to the 92.6 km (50 nautical miles) nonstop range of the notional UAM aircraft. For aerodrome pairs that are more than 92.6 km (50 nautical miles) apart, the UAM vehicle has to make at least one stop to perform a 20-minute recharge. Similar to Fig. 7, however, there is roughly a linear trend from the shortest UAM flights up until the 'duration periphery' caused by the range at which an aircraft would have to land and recharge.

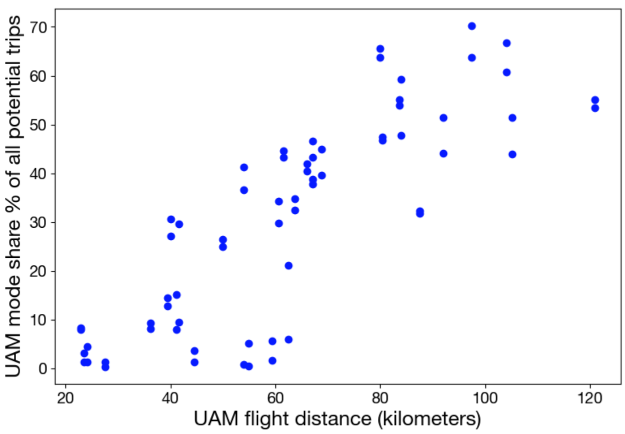


Figure 7 – UAM mode share per route as a function of UAM flight distance in the notional ten-aerodrome network in the Denver metropolitan area. The mode share of UAM against the car-only mode approaches 70% on some longer-distance routes.

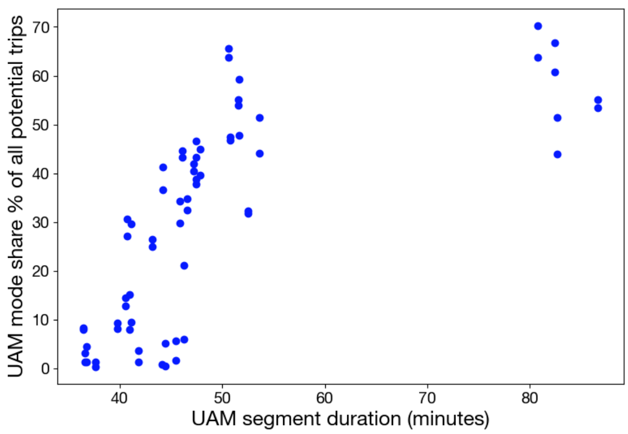


Figure 8 – UAM mode share per route as a function of UAM segment duration in the notional ten-aerodrome network in the Denver metropolitan area. Passengers on longer-distance routes have increasingly greater preference for ridesharing-enabled UAM flying.

The *VoT distribution* is a metric we use to gauge the effectiveness of implementing ridesharing in UAM to expand affordability for passengers (commuters in our case). In Figures 9, 10, and 11, we plot the VoT distribution for UAM-preferring passengers in a non-ridesharing scenario, ridesharing-enabled UAM-preferring passengers, and all passenger-trips modeled in the Denver metropolitan area, respectively.

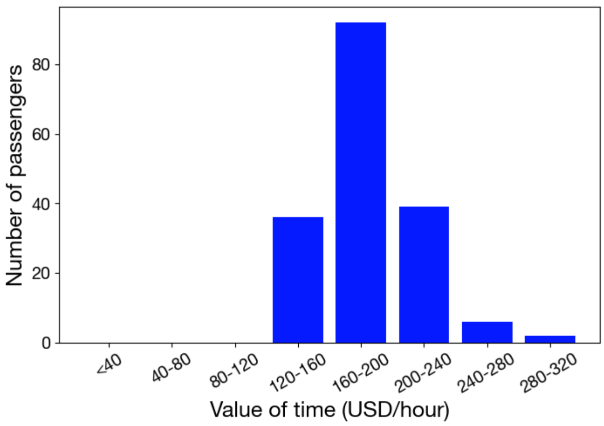


Figure 9 – VoT distribution of 175 UAM-preferred trip passengers without ridesharing for UAM operations in the notional Denver ten-aerodrome network with a mean of 185 USD/hour.

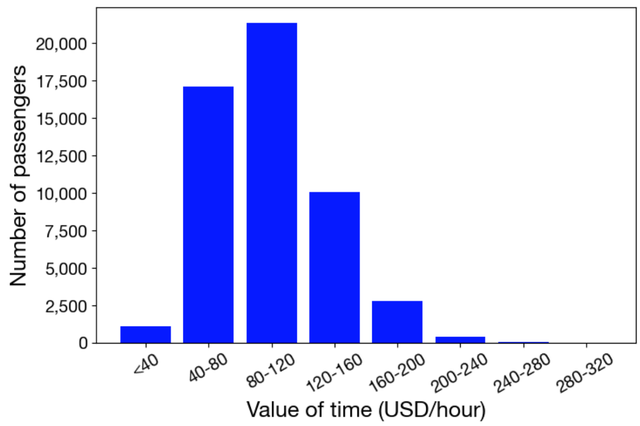


Figure 10 – VoT distribution of 52,709 UAM-preferred trip passengers with ridesharing for UAM operations in the notional Denver ten-aerodrome network with a mean of 98 USD/hour.

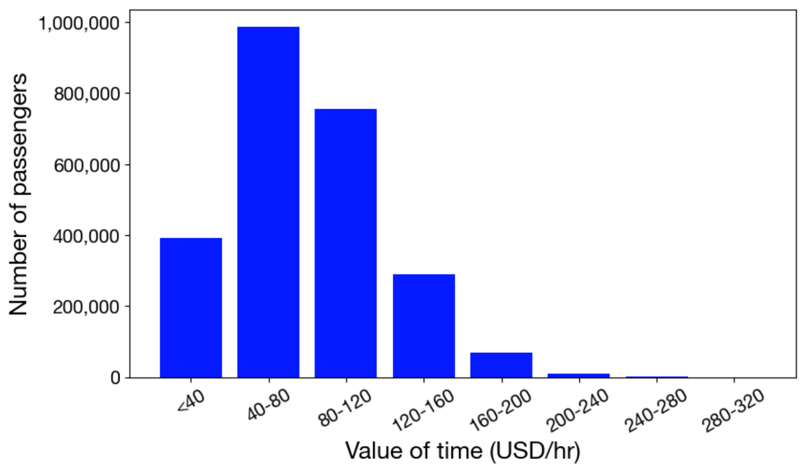


Figure 11 – VoT distribution of all 2,504,562 passengers modeled for the notional networks in the Denver metropolitan area with a mean of 79 USD/hour.

The VoT distribution plots not only show significantly higher passenger numbers for every VoT group when considering ridesharing-enabled scenarios, but also demonstrate a considerable decrease in the mean and modal VoT for passengers selecting UAM. The VoT mode shifts down to the 80-120 USD/hour range in the ridesharing scenario from the 160-200 USD/hour range in the non-ridesharing scenario, and the mean VoT is cut by over 47% to 98 USD/hour from 185 USD/hour.

In addition, the passengers preferring UAM span across a wider spectrum of VoT when ridesharing is enabled as compared to the non-ridesharing scenario. For example, there are passengers in the <40 USD/hour VoT group who select the UAM mode with ridesharing enabled, as opposed no passengers selecting the UAM mode without UAM ridesharing. The impact of this result includes an expansion of the passenger demand demographics to more prominently include passengers with VoTs below 120 USD/hour according to our model. However, the ridesharing-enabled VoT distribution still skews towards higher VoTs as compared to that for all passengers modeled in the Denver metropolitan area (Fig. 11).

5. Conclusions and Future Work

This paper presents (1) a UAM ridesharing methodology (termed PANVEL) which enhances a pre-existing computational framework that assesses mode choice for commute trips within multiple U.S. metropolitan areas; (2) comparisons of estimated UAM market share both with and without ridesharing in these metro areas; and (3) multiple case studies that detail the nature of ridesharing impacts on UAM attractiveness.

We conclude that enabling ridesharing in UAM can considerably increase the number of UAM-preferred passenger-trips across most metropolitan areas and distinct aerodrome networks. However, even with ridesharing, we found that the UAM market share remains below 8% in all use-cases, with an average UAM market share across all six metropolitan areas of approximately 2.6% for the full aerodrome networks. The ridesharing methodology utilized in this study has also been found to produce a relatively high number of four-passenger UAM trips, leading to high load factors across most metropolitan areas and network sizes. Furthermore, case study results in the Chicago and Denver metropolitan areas found that aerodromes closer to city centers tend to see most aircraft and passenger movements. Additionally, for the Denver ten-aerodrome network, we observe a 47% reduction in the mean VoT for UAM-preferring passengers when ridesharing is enabled along with a general shift in demand towards passengers with lower VoT that would prefer UAM.

There are several notable limitations in current analysis presented in this paper. PANVEL assumes perfect knowledge of passenger movements, such as their arrival times, and other passenger characteristics, such as their VoT and origin and destination aerodrome pairs. PANVEL is not a real-time UAM passenger-pooling algorithm; rather, it strictly operates on and analyzes a set of pre-defined trips. In addition, the studies in this paper are ‘unconstrained’ in the sense that they do not consider several practical constraints, such as aerodrome throughput constraints; potential airspace conflicts or other air traffic management constraints; and aircraft availability throughout the aerodrome network; along with policy-/operator-imposed ride-sharing protocols to aggregate passengers. These real-world constraints will lead to a reduced number of achievable UAM trips from those predicted in our modeling. Taken together, these constraints and the limitations with the ridesharing algorithm lead our results to provide a rough ‘upper bound’ on the number of UAM-preferred trips, with fewer trips being expected in real-world operations.

Future work is planned to assess ridesharing-enabled constrained UAM operations given aerodrome throughput operational limits across aerodrome networks and metropolitan areas, in order to obtain a more practical estimation of the number of future UAM operations. Future case studies may also center around certain aerodromes to investigate the differences in aircraft movements and flight routes into and out of those aerodromes with and without ridesharing. The impact of this work extends beyond the aviation community to other stakeholders in AAM. Case studies such as those presented in this paper may also guide city planners in efforts to develop UAM infrastructure across their respective metropolitan areas that have the greatest overall benefit in mobility.

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under the Open Database License [32].

8. Copyright Statement

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