Passenger Aggregation Network with Very Efficient Listing (PANVEL) Ridesharing Model for Urban Air Mobility

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This paper introduces a ridesharing model useful for examining the role of ridesharing in advancing Urban Air Mobility (UAM) operations. Although the success of UAM will likely require a host of new technologies in aircraft design, airspace management, autonomy, and more, operational innovations like ridesharing may also be key, especially to lower operating costs and attract a broader market. The ridesharing algorithm introduced, termed the Passenger Aggregation Network with Very Efficient Listing (PANVEL) model, estimates trip numbers and passenger occupancy aboard particular aircraft within a UAM network in a metropolitan area. This algorithm is applied within a transportation computational framework to determine the impact of ridesharing on mode choice, passenger travel patterns, and transportation costs. The algorithm aggregates passengers traveling between identical origin-destination pairs, factoring in individual-specific metrics, such as value of time and alternative mode options, to generate high load factors on UAM aircraft. The computational framework simulates passenger mode-choice selections using an *effective-cost* approach to determine the number of ridesharing *UAM-preferred trips*, and results with ridesharing are representative of a rough upper bound on UAM ridership potential for a given metro area. A case study in the Cleveland metro area is presented to demonstrate the algorithm and assess ridesharing potential.

Nomenclature

Abbreviations:

AAM	Advanced Air Mobility
CSA	Combined Statistical Area
DPA	DuPage County Airport
eVTOL	electric Vertical Take-Off and Landing
IRS	Internal Revenue Service
MDW	Midway International Airport
PANVEL	Passenger Aggregation Network with Very Efficient Listing
RAM	Regional Air Mobility
UAM	Urban Air Mobility
VoT	Value of Time

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Variables:

$d_{\text{Non-UAM}}$	Road distance for non-UAM trip
$d_{\text{First/Last}}$	First- and last-mile road distance in a UAM trip
k	Passenger capacity of aircraft
P_N	Passenger number N
$P_{\text{Non-UAM}}$	Non-UAM trip price per passenger
P_{OC}	Price per person covering aircraft operating cost
P_{UAM}	UAM trip price per passenger
SM_{RATE}	Standard mileage rate
T_{ED}	Earliest departing time of a passenger
T_{LA}	Latest arrival time of a passenger
$t_{\text{Non-UAM}}$	Total non-UAM trip duration
t_{UAM}	Total UAM trip duration
WT_{MAX}	Maximum wait time

I. Introduction

Advanced Air Mobility (AAM) has the potential to improve how people and cargo move over local and regional distances by shifting trips typically performed on the ground into the air using novel, small aircraft. AAM is often imagined to be similar to a ground-based ride-hailing service with an aerial component, in which users would travel to their nearest aerodrome,* board an aircraft, fly to another aerodrome close to their final destination, and then travel to their intended destination. The first-mile (from trip origin to origin aerodrome) and last-mile (from destination aerodrome to final destination) journeys may be taken with different modes of transport, such as walking, biking, driving, ground-based ride-hailing, or taxi. AAM promises the integration of faster aerial transport in everyday transport that can significantly shorten travel times for passengers.

There are differing views on the scope of AAM, but there is a general consensus that there are at least two subsets of AAM for passenger-carrying missions: Urban Air Mobility (UAM) and Regional Air Mobility (RAM). UAM operations are generally flights up to 75 nautical miles (86 miles) within a single metropolitan area [1]. UAM is primarily envisioned to use electric vertical takeoff and landing (eVTOL) aircraft operating from either novel or repurposed infrastructure to reduce developmental cost, impacts on the existing transportation systems, and concerns about noise and emissions. RAM is envisioned for trips between approximately 50 and 500 miles that primarily leverage existing airports and electric aircraft, which are typically proposed to have conventional takeoff and landing or short takeoff and landing capabilities. In this paper, our primary focus will be on UAM operations, but the methods presented may also be applicable to RAM.

The potential transportation paradigm shift brought about with UAM is driven by advancements in technology, such as materials engineering, battery technology, novel aircraft design, computing, and control theory [2]. These innovations pave the way for a new era in both passenger and cargo transport by leveraging novel, electrified, highly automated aircraft [3]. UAM flights present advantages over traditional mobility solutions, particularly in congested urban areas, due to the possibility for significantly faster travel times and reduced environmental impact [4]. Long commute times have been shown to negatively impact quality of life [5, 6] and productivity [7]. For example, the two most congested cities in the US in 2022 were Chicago and New York, where the average driver spent approximately 155 hours and 117 hours in traffic, respectively. The impact of the time spent in traffic cost the cities \$9.5 billion and \$10.2 billion, respectively, in lost productivity [7]. Given the projected speed advantage of aerial transport, UAM could reduce these times and assist in increasing overall productivity.

In addition to potential transportation benefits for travelers, UAM could also have environmental benefits [8], particularly when compared to gasoline-powered cars and considering direct vehicle “tailpipe" emissions; however, evidence for such benefits has yet to emerge in a comprehensive fashion (and work continues to develop appropriate metrics to make the assessment [9]). Many envision UAM leveraging electric aircraft with zero tailpipe emissions [3]. This is an attractive proposition in polluted and congested urban areas. As Mudumba et al. demonstrate, coupling electric UAM aircraft with “green” electricity generation can provide reduced carbon dioxide emissions compared to existing internal combustion engine (ICE) ground vehicles [10]. One potential way to reduce emissions via UAM is by leveraging ridesharing.

Ridesharing is an attractive proposition for UAM operations because it can encourage broader UAM ridership, mitigates economic challenges, and serves as an environmentally conscious transportation alternative. Ridesharing can distribute operating costs and emissions among more passengers, making UAM more affordable and environmentally friendly on a per-passenger basis. These advantages make it crucial to analyze the ridesharing potential of an area and quantify these impacts, which can help identify the most suitable metro areas for UAM operations. The main

*We use the term aerodrome to refer to any facility from which a UAM aircraft may take-off and land, including vertiports, conventional airports, and heliports.

contribution of this paper is to introduce an algorithm aimed at evaluating the feasibility of ridesharing for UAM operations. This paper is organized as follows:

Section II covers a brief background and motivation behind the ridesharing algorithm proposed in this study, and Section III illustrates the methodology behind the PANVEL algorithm. Section IV provides an example application of the algorithm to trips within the Cleveland metro area. Section V highlights the conclusions of this study.

II. Background and Motivation

The concept of integrating routine aerial transport in urban and regional settings is an idea that has been explored previously in the US in the 1960s and 70s in the form of helicopter airlines in metropolitan areas such as Chicago, New York, Los Angeles, and San Francisco [11, 12]. Due to various factors, such as government withdrawal of subsidies, rising fuel prices, noise concerns, and high-profile accidents, helicopter airlines did not survive, and the industry all but went bankrupt by 1975 [13]. Recently, advancements in aircraft design, autonomous operations, policy changes, etc. have created interest in looking once again at air mobility in urban settings. For instance, advances in electric propulsion technologies hold promise for improvements in noise, safety, and sustainability. Research has followed targeting strategies for the successful implementation and integration of UAM in widespread adoption [14–17]. Previous studies exploring potential UAM implementations have shown that feasibility depends on many factors, such as weather patterns [18], traffic congestion, income, geography, population size [19], airport or vertiport throughput [20] and air traffic management. Many of these factors have been evaluated and quantified in previous literature [19, 21].

For many types of UAM operations, it is anticipated that the UAM transportation mode will be more expensive than traditional mode choices, but the added expense for UAM may be preferable to some in order to benefit from more rapid transportation. Thus, individuals with higher value of time (VoT) are more likely to leverage UAM services than those with a lower VoT because individuals with higher VoT would theoretically be willing to incur additional cost to save time. Due to relatively high operational expenses that are anticipated in the near term, the potential customer base for UAM services may be limited. For UAM operations to become practically accessible to many individuals, efforts to reduce costs and increase ridership are crucial. UAM operations will not be economically sustainable without a consistent ridership. High prices reduce the level of ridership, and low ridership can lead to cost increases, such as through increasing non-revenue-generating repositioning flights. Conversely, lower prices will attract more passengers leading to better utilization of resources and, consequently, increased revenue.

Research by Maheshwari et al. [19] suggests that lower per-passenger UAM fares, made possible by increasing the number of passengers per aircraft trip, can increase the number of passenger-trips favoring the UAM mode of transportation, termed *UAM-preferred trips* hereafter. However, the work in Ref. [19] estimated simple fare reductions for all passengers and did not consider the practicality of ensuring a sufficient number of passengers could be aggregated on aircraft to meet the general fare reduction assumptions. Therefore, we seek to overcome these limitations by investigating factors related to route networks, passenger travel patterns, and VoT to quantify the feasibility of ridesharing in a given area.

Although several ridesharing models exist in literature, few have been found to be suitable for large-scale analysis of an entire metropolitan area. Each area has its unique set of characteristics, such as aerodrome locations, congestion levels, travel patterns, etc., which can add variability to UAM implementation in that region. For instance, Yang et al. [22] developed a Mixed Integer Bi-linear Programming (MIBLP) model to optimize wait times for ridesharing in an UAM network leveraging four-passenger aircraft. This approach uses a theoretical dataset of passengers within a conceptual vertiport network. The model accounts for various transportation modes, including bicycles, buses, subways, cars, and walking. Furthermore, the research incorporates control laws and algorithms to simulate operational flight paths. There is also a module that uses a real-time aircraft path planning algorithm to calculate an air route. This model focuses on a possible deployment method for UAM service considering additional parameters like vehicle availability, idle time, etc. Although this model was found to be too complex for our purposes, it represents a possible starting point for extending our ridesharing model and enhancing the operational realism of our UAM operation simulations.

Previous work by Maheshwari et al. [23] implemented a reinforcement-learning-based ridesharing algorithm in conjunction with an on-demand air service trip generator to assess ridesharing feasibility from an operational standpoint. This method considers aerial ridesharing on two-passenger aircraft for a hypothetical vertiport network, and it integrates penalty functions to maximize ridesharing operations. Given the machine learning model it implements, the algorithm is computationally too expensive to be deployed over large datasets encompassing a complete metro area as are the focus of our work.

Bennaceur et al. [24] proposed another mixed-integer linear programming model for on-demand air-taxi services, focusing on passenger pooling and aircraft scheduling. They suggested different service classes, similar to Uber's ride-hailing model, in which higher fares result in shorter wait times, aiming to enhance affordability and accessibility. Unlike their approach, which only considers travelers desiring to travel via air taxis, our study analyzes all commute trips, assigning mode preferences for each passenger.

Additionally, we reviewed ridesharing models for ground transport. Kuehnel et al. [25] introduced the Flow-Inflated Selective Sampling (FISS) method, which simulates ground trips within a city, with tracking limited to 500 rideshared vehicles to save on computational effort. This method tracks the vehicles through a region, as compared to our approach of tracking individual passengers. Tracking passengers is important because UAM trip feasibility depends on the first- and last-mile journeys and not just on the aerial segment. Furthermore, the computational cost of leveraging the FISS method to track millions of passengers, as is our goal, would be impractically high. Liu et al. [26] examined agent-based models for carpooling in Austin, comparing shared autonomous vehicles (SAVs) and private human-driven vehicles (HVs) across different fares and distances, aiming to maximize utility for all passengers. Their results indicate the preference for SAVs over HVs for multiple fare classes. Utilizing agent-based simulation methods delivers high fidelity, but at considerable computational expense, which would make simulating UAM operations in large metro areas prohibitively expensive and time-consuming. Furthermore, this work focused more on vehicular ridesharing preferences rather than on ridesharing potential and feasibility. In road transport, passengers have greater flexibility in determining pick-up and drop-off locations compared to UAM trips. Mode changes are less of an issue since road travel is better suited for door-to-door service.

We aim to develop an algorithm capable of operating on large, passenger-based datasets to assess the theoretical potential for ridesharing in specific metropolitan areas. This algorithm will integrate with the strategic analysis framework we developed in prior work [19, 27]. Our current and previous work frames the development of UAM as a System of Systems (SoS) problem [28]. As an SoS problem, UAM implementation involves different hierarchical levels of organization ranging from strategic at the highest levels of hierarchy to operational at the lowest level.

On the strategic level, our research focuses on identifying factors that could limit UAM operations, especially those with significant impacts. Such factors could lie in economic, environmental, regulatory/policy, or operational domains. Essentially, we seek to understand in what circumstances a UAM service should even be considered, given particular market and demand scenarios in individual metro areas. This strategic analysis can be considered a precursor to developing lower-level operational innovations and technological infusion as discussed in the referenced literature. Using the analogy from the verification and validation (V&V) process described in Ref. [29], we first aim to answer whether a UAM system should be built and then determine what the UAM system should look like.

This paper introduces a model capable of quantifying the potential impact of ridesharing on UAM operations, analyzing economic attractiveness regarding potential passenger utilization while being computationally efficient in order to analyze operations in large metro areas. The algorithm is named Passenger Aggregation Network with Very Efficient Listing (PANVEL), and through it we aim to compute an upper limit on the total possible trips enabled by ridesharing in particular metro areas.

PANVEL is integrated within a larger computational framework workflow for UAM analysis that includes the input datasets listed in Fig. 1. Within this framework, the cost of a transportation mode includes both the direct fare and the cost of the time spent on that mode, considering every passenger's VoT. This metric, termed the "*effective cost*," is used by PANVEL to make decisions regarding ridesharing. Fig. 1 shows the integration of the PANVEL algorithm within the wider computational framework. The framework utilizes data obtained from diverse sources as described in Ref. [19]. These sources generate passenger trips considering various factors, such as household income and congestion patterns, which serve as an input.

The computational framework determines the nearest available vertiport and computes the travel times for each passenger via car-only travel and multi-mode UAM travel. The framework also calculates costs for UAM and car travel, and, by combining travel time and cost into a single effective cost metric, individual passenger mode choices are determined. Additionally, the framework leverages supplementary modules to assess operational limits related to weather, emissions, aerodrome throughput and capacity, and cost analysis. Readers are encouraged to refer to [19, 20, 27, 30–34] for a comprehensive understanding of the computational framework. The next section provides a detailed explanation of how the PANVEL algorithm functions within this framework.

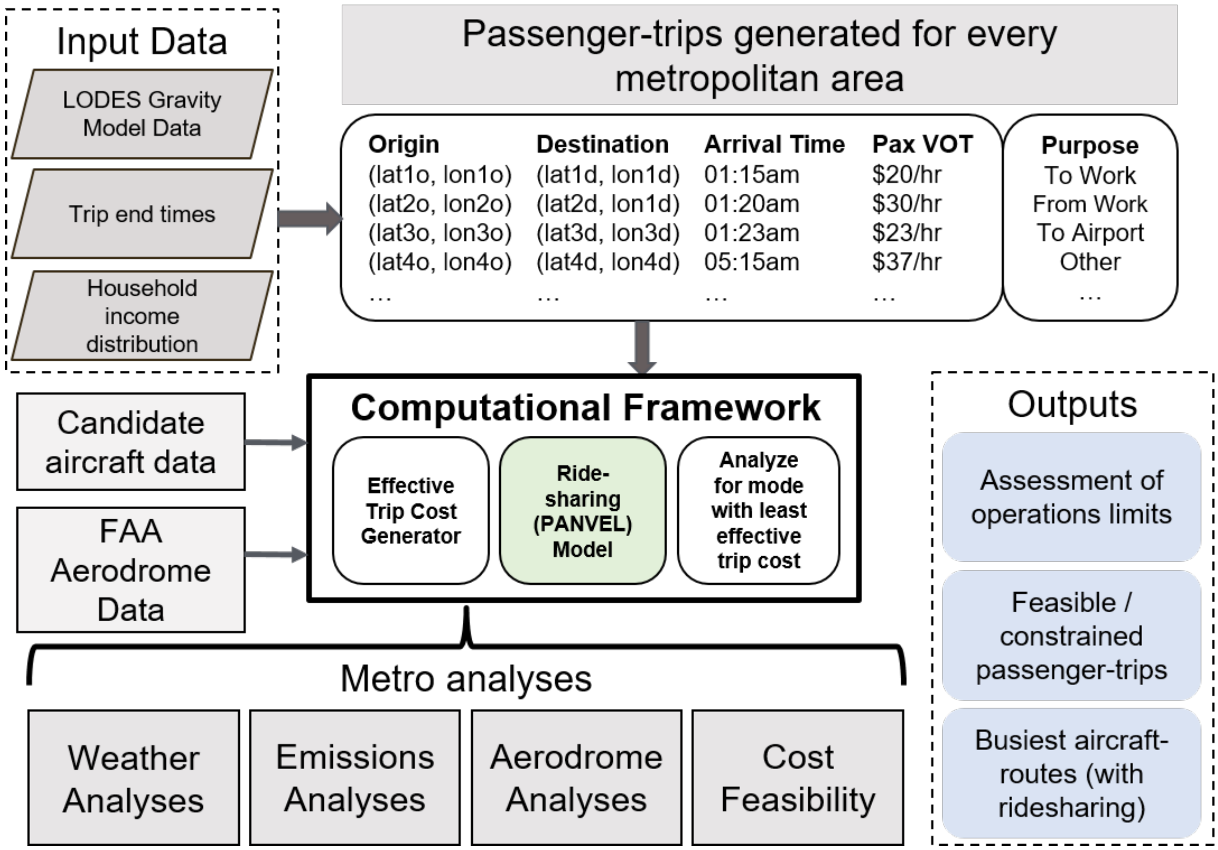


Fig. 1 The PANVEL ridesharing model situated within the larger UAM operations computational framework, including the major input and output categories of the framework.

III. Methodology

The PANVEL algorithm aggregates passengers traveling from one location to another based on estimates of their values of time and their arrival times at the origin aerodrome. The algorithm's unit of analysis is an individual passenger trip requiring mode changes, and its execution is integrated with the computational framework referenced previously, which determines individual passenger mode choices based on the effective cost metric. The computational framework generates a list of all passenger trips in a given metro area and identifies opportunities where a segment of each trip could be substituted with an aerial mode. A subset of trips is generated for which the traveler would experience reduced travel time from the UAM mode. The PANVEL algorithm analyzes this subset of trips that provide a time advantage via UAM to estimate which passengers may prefer to share an aircraft with others to reduce the fare they pay for the flight. Generally, passengers' travel times will increase with ridesharing, so PANVEL considers passengers' arrival times to aerodromes and their values of time to determine if ridesharing is practical and preferable for each traveler. Ultimately, the PANVEL algorithm estimates the unconstrained total number of UAM flights with ridesharing as well as the associated total number of passengers and the cost for each passenger.[†] Figure 2 illustrates the three different trip mode choices considered in this paper.

In the following subsections, we describe the PANVEL algorithm's assumptions, pre-processing, and execution. These subsections reference a sample, simplistic UAM mission between the Midway International (MDW) and DuPage (DPA) airports in the Chicago, IL metro area to help illustrate the various features of the PANVEL algorithm. This example assumes a notional, four-passenger eVTOL aircraft taken from Roy et al. [32] with an operating cost of $605/hr, which is derived from Uber Elevate's "launch cost" scenario [35].

[†]In this context, the term "unconstrained" is used to acknowledge that there are other operational factors, such as aerodrome throughput limits and air traffic management constraints, that may ultimately reduce the number of practically realizable flights from those predicted.

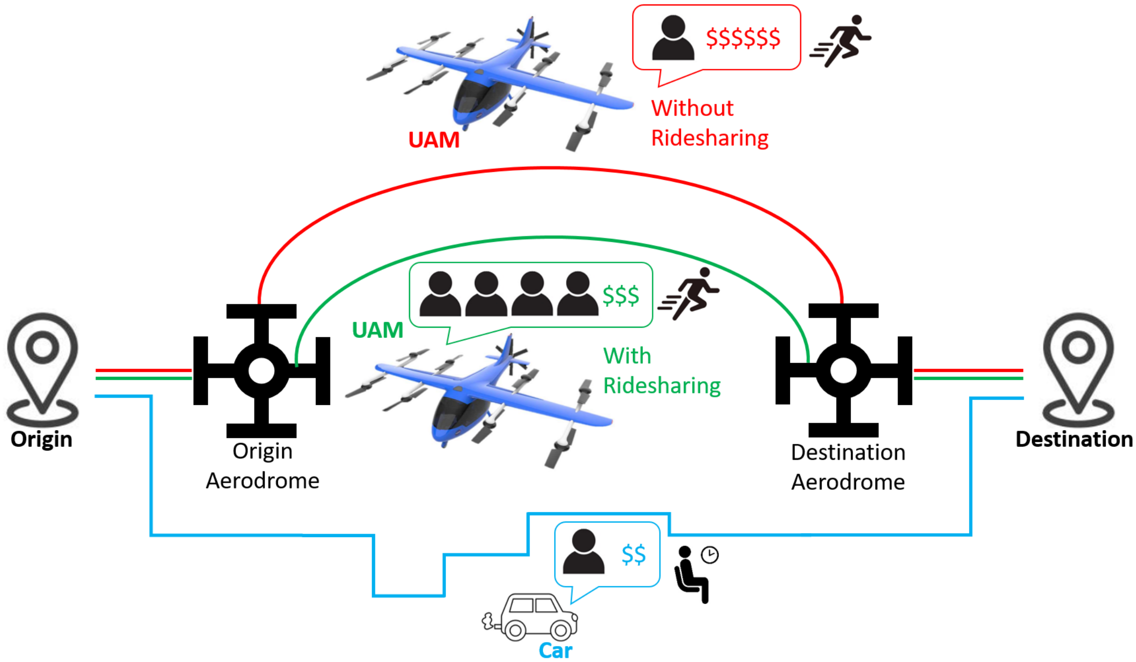


Fig. 2 Three different trip mode choices analyzed with the PANVEL algorithm.

A. Assumptions

The PANVEL algorithm includes the following assumptions:

- The full-aircraft operating costs remain constant regardless of load factor.
- The full-aircraft operating costs are divided evenly among all the passengers aboard the aircraft.
- Passengers select the travel mode with the least effective cost.
- Passenger arrival times at the gate at origin aerodromes are known; thus, passengers arrive and progress through the aerodrome without any delays.
- The trip cost by car is determined by a fixed cost per mile multiplied by the mileage driven.‡

B. PANVEL Pre-processing Step

The pre-processing required to execute the PANVEL algorithm is conducted within the computational framework. The computational framework calculates the projected cost and travel time for each potential travel mode (see Figure 2). Travel time calculations consider ground traffic based on road congestion data [37].

PANVEL also requires the data for each passenger trip listed in the column headings of Table 1. The data points under each column heading are for a sample case in the Chicago metro area. The initial six columns of this table are directly derived from other elements the computational framework and serve as inputs to PANVEL. The *Lowest Non-UAM Trip Cost* denotes the lowest expense associated with traveling by a mode other than UAM. For our current modeling, this cost is that by traveling via car since no additional modes are considered. The *Max Wait Time* for each passenger represents the maximum duration they are willing to wait at an aerodrome for the UAM flight to begin. This wait time is determined by a function involving a passenger's VoT, the anticipated trip duration, and the effective cost they would incur as shown in Eq. (1).

$$WT_{\text{MAX}} = (t_{\text{Non-UAM}} - t_{\text{UAM}}) - \frac{P_{\text{UAM}} - P_{\text{Non-UAM}}}{VoT} \tag{1}$$

In the above equation, WT_{MAX} represents a passenger's maximum waiting time, $t_{\text{Non-UAM}}$ stands for the duration of a trip completed entirely using the non-UAM mode with the lowest trip cost, t_{UAM} signifies the trip duration utilizing the aerial mode and associated first- and last-mile segments, P_{UAM} is the price to a passenger for the entire UAM trip

‡For this analysis, we assume costs at the Internal Revenue Service (IRS) standard mileage rate of $0.58 per mile [36].

(including first-mile, air, and last-mile segments), and $P_{\text{Non-UAM}}$ is the price to the passenger for a trip via the non-UAM mode with the lowest trip cost.

Table 1 Excerpt of the input file used for the Midway-DuPage case study

Data #	Arrival Time at Origin Aerodrome Gate (hh:mm)	Origin Aerodrome	Destination Aerodrome	Lowest Non-UAM Trip Cost ($)	Value of Time ($/hr)	Maximum Wait Time (min)
1	06:04	MDW	DPA	29	46	10
2	07:04	MDW	DPA	261	204	5
3	07:13	MDW	DPA	291	224	15
4	08:34	MDW	DPA	300	236	16
•	•	•	•	•	•	•
•	•	•	•	•	•	•
95	17:29	MDW	DPA	68	74	11

For our sample case that considers only a car mode as an alternate to UAM and leverages cars for the first- and last-mile segments of a UAM trip, Eq. (1) can be written as Eq. (2).

$$WT_{\text{MAX}} = (t_{\text{Non-UAM}} - t_{\text{UAM}}) - \frac{P_{\text{OC}} - SM_{\text{RATE}}(d_{\text{Non-UAM}} - d_{\text{First/Last}})}{VoT} \tag{2}$$

In Eq. (2), P_{OC} stands for the per passenger fare for the aircraft, $d_{\text{Non-UAM}}$ denotes the distance covered on the trip when travelled in its entirety by car, $d_{\text{First/Last}}$ denotes the distance travelled by road during the UAM first- and last-mile segments, and SM_{RATE} denotes the cost per mile of ground transport.

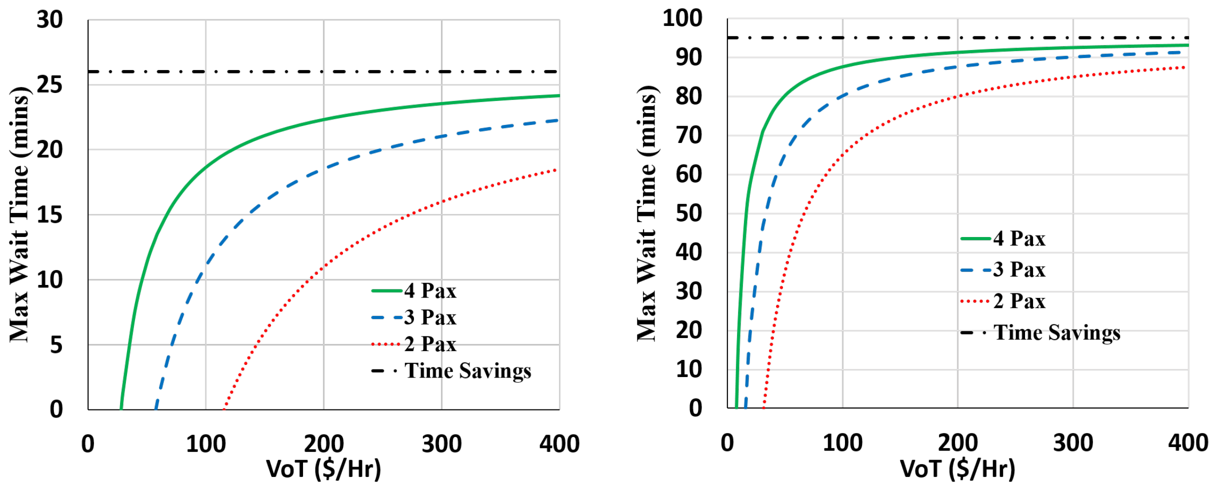
These equations reflect the assumption that a passenger has the flexibility to wait longer in the UAM mode at the aerodrome if the following two criteria are fulfilled:

1) The UAM trip's total effective cost, inclusive of the wait time, is lower than the most economical available alternative (which is the car mode in our example).
2) The passenger arrives at their destination earlier than the most economical alternative to the UAM mode.

Equation (2) leads to an interesting finding. The wait time comprises two competing terms. The first term [$t_{Non\text{-}UAM}$ - t_{UAM}] refers to the time savings from the UAM mode of travel. The numerator of the second term [$P_{\text{OC}} - SM_{\text{RATE}}(d_{\text{Non-UAM}} - d_{\text{First/Last}})$] represents the cost difference between the UAM mode and the Non-UAM mode. Dividing this cost difference by VoT yields the time savings required to justify the higher costs. In other words, the second term can be thought of as the time penalty associated with the cost increase due to the UAM mode. The second term is then subtracted from the first term (total trip time savings) to yield the maximum wait time. Given the current nature of UAM costs, the term P_{OC} has been observed to be higher than the value obtained from $SM_{\text{RATE}}(d_{\text{Non-UAM}} - d_{\text{First/Last}})$, primarily due to the SM_{RATE} being relatively low. This ultimately contributes to the numerator of the second term being positive, which reduces the max wait time when it is subtracted from the time savings. Consequently, the higher a traveler's VoT is, the greater that traveler's Maximum Wait Time is. This leads to the finding that though the VoT is inversely proportional to the discounted operating cost, VoT and the max wait time are positively correlated. Although it may seem counter-intuitive at first, by making mode choice a function purely of the effective cost, individuals with a higher VoT can still prefer the UAM mode with longer waiting periods, as long as the total effective cost is lower than the alternative mode, which typically results from a reduction in the overall door-to-door travel time. In other words, despite the wait time, the total trip duration is still less than the alternative mode. The trip time saved through UAM holds significantly more value for those with a higher VoT. Therefore, even though the wait time may erode some of these time savings, it remains preferable to a certain extent. For individuals with a higher VoT, waiting longer for an UAM trip outweighs spending more time driving when considering the door-to-door time savings based on our effective cost model.

To illustrate this concept, we applied Eq. (2) to a hypothetical scenario involving a trip from Midway International Airport (MDW) to DuPage Airport (DPA) in the Chicago metro area. This trip could be completed either by aircraft or by car, without including any first- or last-mile ground segments for the UAM mode. First- and last-mile ground journeys were deliberately excluded to focus on the relationship between wait times and VoT without additional variables, such as distance between the origin and origin aerodrome or the destination aerodrome and destination.

The flight duration between MDW and DPA is 15 minutes, whereas driving times vary between 41 and 110 minutes based on traffic conditions. Thus, UAM offers a time savings of 26 to 95 minutes. However, this time savings is often reduced in ridesharing due to the need to wait on other passengers to arrive.§ Longer wait times result in less time savings, making it less likely that a passenger would be willing to pay given their VoT. Thus, the maximum time a passenger would be willing to wait is a function of their VoT. The variation of the maximum wait time for passengers as a function of their value of time is plotted in Fig. 3, where Fig. 3(a) shows the case of free-flow road conditions and Fig. 3(b) shows the case with highly congested roads representative of "rush hour" conditions.



(a) Free-flow traffic conditions on route between MDW-DPA

(b) Typical peak congestion on route between MDW-DPA

Fig. 3 Maximum wait times for UAM flights between MDW and DPA as a function of passenger value of time with various numbers of passengers sharing an aircraft and varying ground traffic conditions.

In Fig. 3, the x-axis of both plots represents the VoT of potential riders, while the y-axis shows the maximum wait time in minutes that a passenger with a given VoT would be willing to wait for a UAM flight. There are three colored lines on each plot indicating the maximum wait time for a passenger to prefer the UAM mode based on ridesharing with four, three, or two passengers on board the aircraft. These lines are distinct because a single passenger would bear 25%, 33%, or 50% of the full cost of operating the aircraft, respectively, in these different scenarios. In moving from four passengers (shown with the green solid line) to three passengers (shown with the blue dashed line), there is a decrease in the maximum wait time due to the increased fare; another decrease in maximum wait time occurs in moving from three passengers to two (shown in the red dotted line) for the same reason. The black horizontal broken line represents the time saved by UAM assuming zero wait time, which is also the theoretical maximum wait time. If wait times reach this limit, the total transit time for the UAM and car modes becomes the same, and a hypothetical passenger with an infinite VoT would be indifferent to the mode choice. However, because the UAM mode has an increased cost compared to the ground mode and no passenger has infinite VoT, the practical maximum wait time does not ever reach the theoretical maximum wait time.

Additionally, the x-intercepts on these plots indicate the minimum VoT required for an individual to select a UAM trip. The minimum VoT metric can serve as a filter to reduce computational time by screening out passengers whose estimated value of time is not commensurate with choosing a UAM trip. The minimum VoT necessary for an individual to prefer a UAM trip is determined by factors such as door-to-door time savings, and vehicle occupancy. This point denotes a "break even" point at which the value a traveler places on the time saved by the faster speed precisely equals the additional expense incurred for that saved time. For individuals with VoT at or below this minimum VoT, a car-based trip would be preferable even if there was no waiting period for a UAM flight. For passengers with negative wait time values, the time savings is not worth the expense; such passengers are thus not considered in ridesharing.

Longer wait times increase the likelihood of more passengers arriving in time for a shared trip while eroding

§There are also other time penalties in UAM, most notably the time associated with changing modes from ground to air and air to ground. In this simplistic example, these additional time penalties are not included.

potential time savings. Though the longer wait times offer greater flexibility to the operators assigning riders, the margin on time savings will determine if travelers reconsider using the UAM segment. Wait time durations vary based on the number of passengers being considered for the trip.

For our sample use case, the PANVEL algorithm considers a four-passenger aircraft. The algorithm aggregates trips with four passengers, followed by trips with three passengers, and finally two passengers. As the number of passengers in a ridesharing vehicle decreases, the cost per passenger increases accordingly. With these increased costs, passengers expect greater time savings to justify the expense. Consequently, passengers are willing to wait for even less time with fewer total passengers on the aircraft because of the diminishing time savings. The PANVEL algorithm prioritizes trips with higher load factors and only rideshares trips with fewer passengers if higher load factor ridesharing alternatives are not available because of limited wait times and passengers arriving to the aerodrome with the same desired destination aerodrome.

C. PANVEL Ridesharing Algorithm Execution Step

The PANVEL algorithm flowchart is shown in Fig. 4. The algorithm operates chronologically based on each passenger's arrival time at the origin aerodrome gate (column 2 in Table 1). The parameter k defines the number of passengers for the prospective flight. For our example problem, the algorithm begins with four passengers as a group (i.e., $k = 4$ initially).

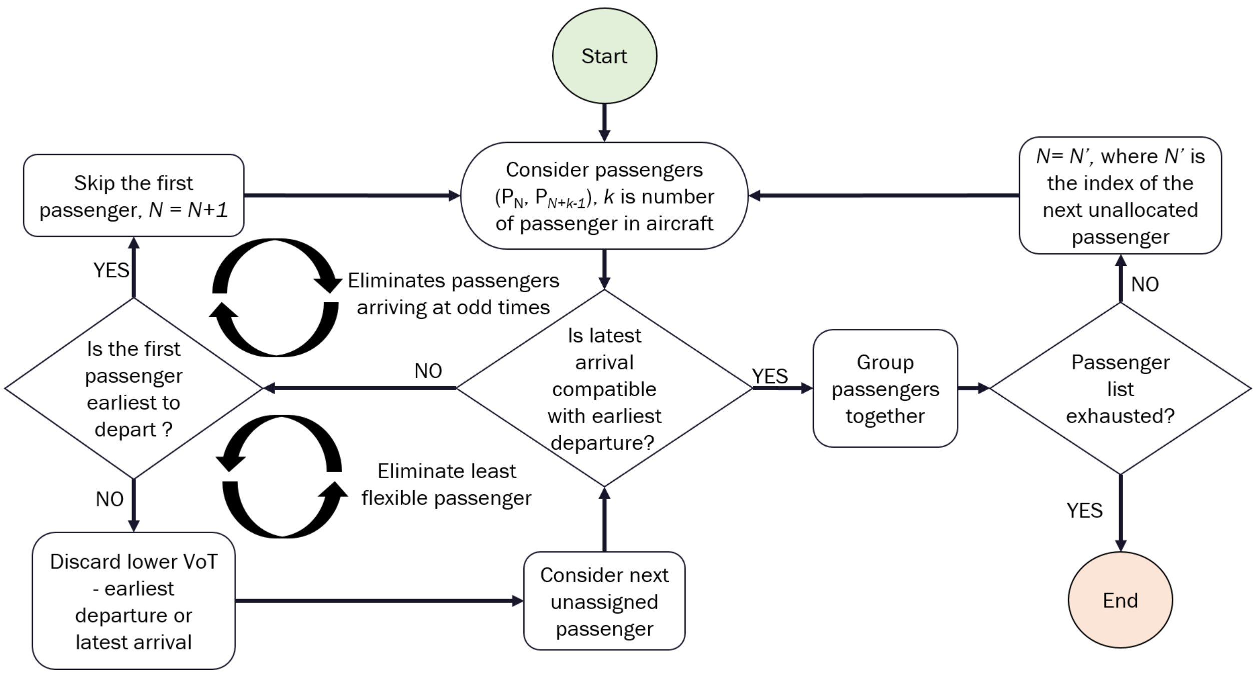


Fig. 4 PANVEL algorithm execution logic.

For the group of k passengers, the passenger who needs to depart first, referred to as the *earliest departure*, is identified by adding each passenger's maximum wait time[¶] to their arrival time at the origin aerodrome gate and finding the earliest time, T_{ED}. Subsequently, this earliest departure time is compared to the arrival time, T_{LA}, for the passenger arriving last, who is referred to as the *latest arrival*. If these two passengers are compatible (i.e., $T_{\mathrm{ED}} \geq T_{\mathrm{LA}}$), the allocation proceeds successfully, and the algorithm moves on to the next unallocated passenger group. However, if these two passengers (i.e., *earliest departure* and *latest arrival*) are incompatible (i.e., $T_{\mathrm{ED}} < T_{\mathrm{LA}}$), the current group of k passengers cannot all rideshare in the same aircraft.

Assuming the original group of k passengers are incompatible, the algorithm then verifies if the first passenger to arrive at the aerodrome is the *earliest departure*. If so, this passenger will never prefer to wait long enough for a compatible group of k passengers to be found; therefore, the first passenger is eliminated from consideration, a new group of k passengers is formed starting with passenger P_{N+1} through passenger P_{N+k}, and the process then begins

[¶]which is found from Eq. (2) with P_{OC} at the appropriate value for a k passenger flight again with this new group. If, however, the first passenger to arrive at the aerodrome is not the *earliest departure*, then either the *earliest departure* or the *latest arrival* is eliminated from consideration for the current trip. Given the large number of passengers at some origin aerodromes, some passengers arrive or need to leave at the same time. Since the algorithm eliminates only a single passenger at a time from being considered for ridesharing, we leverage the passenger VoT as another criterion on which to eliminate passengers from ridesharing consideration to deal with simultaneous arrivals or departures. Specifically, PANVEL eliminates the passenger with the lower VoT between the *earliest departure* and the *latest arrival* to serve as a "tie-breaker" between passengers. [‖]

Ultimately, the PANVEL logic allocates a particular passenger to share a ride in a UAM flight only if the following criteria are met:

1) **Time Compatibility**: A passenger will be assigned to a ridesharing trip only if the aircraft leaves the gate within their maximum allowable wait time.
2) **Effective Cost Compatibility**: A passenger will take a UAM trip only if the effective UAM trip cost is lower than the effective trip cost by car mode only (as before) [19].

The following narrative illustrates the PANVEL process (Fig. 4) with the input scenario outlined in Table 2. This example considers a subset of trips for our sample simplistic mission between Chicago's Midway (MDW) Airport and DuPage Airport (DPA) introduced above (including in Table 1). The *Pax #* column represents the passenger ID. The *Arrival Time (hh:mm)* column provides the passenger arrival time at the origin aerodrome gate, which represents the earliest time at which a rider is available to take a ride. The *Lowest Non-UAM Trip Cost ($)* column represents the cost if the trip were completed entirely in a car (car mode).

Table 2 Test case for UAM operations between MDW and DPA airports

Pax #	Arrival Time (hh:mm)	Origin Aerodrome	Destination Aerodrome	Lowest Non-UAM Trip Cost ($)	Value of Time ($/hr)	Maximum Wait Time (min)	Latest Departure Time (hh:mm)
P_1	08:05 AM	MDW	DPA	98	164	33	08:38 AM
P_2	08:12 AM	MDW	DPA	95	123	10	08:22 AM
P_3	08:13 AM	MDW	DPA	105	132	6	08:19 AM
P_4	08:20 AM	MDW	DPA	103	138	9	08:29 AM
P_5	08:27 AM	MDW	DPA	100	104	1	08:28 AM
P_6	08:30 AM	MDW	DPA	102	124	2	08:32 AM
P_7	08:31 AM	MDW	DPA	101	142	22	08:53 AM
P_8	08:37 AM	MDW	DPA	97	126	12	08:49 AM
P_9	08:37 AM	MDW	DPA	101	177	29	09:06 AM
•••	•••	•••	•••	•••	•••	•••	•••

The algorithm begins by grouping passengers P_1 through P_4 together. It then determines which passenger out of these four needs to depart earliest. In this group, P_3 is the earliest to leave at 08:19. However, this conflicts with the arrival time of the last passenger in the group (P_4), who arrives at the aerodrome at 8:20, rendering the initial group unsuitable for ridesharing. The conflicting passengers are P_3 and P_4. The PANVEL algorithm eliminates P_3 due to their lower VoT and considers P_5 as part of the group instead. This process repeats, with the earliest departing passenger being P_2 (at 8:22), who conflicts with passenger P_5. P_5, having a lower VoT than P_2, is eliminated and replaced with P_6. The current group consisting of P_1, P_2, P_4, and P_6 is still not feasible, as passengers P_2 and P_6 are in conflict. P_2 is eliminated owing to their lower VoT, and P_2 is replaced with P_7. In this new group (P_1, P_3, P_4, and P_7), the earliest departing passenger is P_4 who is in conflict with P_7. P_4 has a lower VoT than P_7; so, P_4 is removed and replaced with P_8. Comparing among P_1, P_6, P_7, and P_8 results in a conflict between P_6 and P_8. Since P_6 has the lower VoT out of the two, P_6 is eliminated and replaced with P_9. This current group, consisting of P_1, P_7, P_8, and P_9, is time compatible and allocated a trip.

‖The rationale behind VoT-based elimination is that passengers with lower VoT values also have shorter wait times based on our estimation from Eq. (2), rendering them less flexible for ridesharing as defined in this model. Furthermore, removing one passenger from consideration will introduce a new passenger, thereby increasing waiting times further. Consequently, passengers with higher VoT values are better equipped to tolerate the now-increased waiting period according to our model that expresses wait time as a function of VoT.

Now that P_1, P_7, P_8 and P_9 have been allocated a trip, the PANVEL algorithm moves on to P_{10} for the next round of allocations, considering first the group of passengers P_{10}, P_{11}, P_{12}, and P_{13}. The process continues as above. If a situation had arisen in which P_1 was not able to be allocated to a shared flight, then the algorithm would restart, beginning with P_2 in a group with P_3, P_4, and P_5.

Once the passenger list has been exhausted, the PANVEL algorithm outputs a list of all four-passenger flights. Then, for unallocated passengers, it recalculates the wait times considering three-passenger flights in a four-passenger aircraft. Since there are fewer riders among which to divide the costs, the per-passenger UAM costs are higher, and the maximum wait times are lower. After exhausting the passenger list for three-passenger flights, passengers not allocated in four-passenger or three-passenger trips are considered for two-passenger trips. Following two-passenger trips, ridesharing is no longer possible. For single-passenger trips, which do not have any wait time, we refer to the output of the computational framework, as described by Maheshwari et al. [19]. Following this, we assemble a list of single-passenger riders by removing those passengers who have already been allocated to a four-, three-, or two-passenger UAM trip from the list of all UAM-preferred trips.

IV. Results

A case study for the Cleveland Combined Statistical Area (CSA) was performed using the computational framework in concert with the PANVEL algorithm. The results for this case study are presented in this section. A forthcoming paper due to be published in the proceedings of the 34th Congress of the International Council of the Aeronautical Sciences (ICAS) is planned to showcase ridesharing results for several other metro areas. The computational framework input data sources match those detailed in Ref. [19], and results are based on operations with the same notional four-passenger aircraft leveraged in Section III.

It is important to note that these results represent unconstrained operations considering ideal ridesharing conditions assuming previously scheduled passenger movements. They do not take into account factors such as aerodrome throughput capacities, pad/runway availability, weather conditions, etc. Thus, the results in this section present a near upper bound on UAM passenger ridership in the Cleveland CSA within the assumptions of our modeling. Additionally, we do not consider ridesharing in the road segments of either mode, which could impact results.

Our analysis has identified a total of approximately 1.98 million passenger trips daily among the Cleveland CSA's estimated 3.58 million residents. Within this region, we identified a total of 72 publicly accessible aerodrome locations that could suitably be converted to support UAM operations. These 72 aerodromes correspond to 1,073 origin-destination pairs potentially viable for UAM operations.[**] Leveraging this network of 72 aerodromes, the computational framework calculates all possible passenger trips that could offer time savings with a UAM trip. For Cleveland, 158,371 passenger trips were identified out of the 1.98 million passenger trips, wherein a portion of the car journey could be replaced by an aerial segment to result in time savings. These 158,371 possible UAM trips serve as the input file to the PANVEL algorithm.

Utilizing these parameters, the PANVEL algorithm generated results for implementing ridesharing in the Cleveland metro area. Although our analysis suggests that, for Cleveland, UAM would not be preferred for any traveler without ridesharing (i.e., no single-rider trips would be UAM-preferred in the area), a small number of trips would be UAM-preferred trips with ridesharing enabled. The results are highlighted in Table 3.

Table 3 Cleveland UAM ridesharing-enabled results

# Passengers in Aircraft	Four (4)	Three (3)	Two (2)	Single (1)	Total
# of UAM Trips	52	2	0	0	58
Passengers Ferried	208	6	0	0	214

Preliminary results for other metro areas indicate increases in UAM-preferred trips via ridesharing as well. The PANVEL algorithm appears to reflect the potential for ridesharing by reducing the travel cost proportional to the number of people flying together. Within Cleveland, we can further identify the aerodrome pairs best suited for ridesharing as seen in Fig. 5. This leads us to summarize the busiest unidirectional flight routes in the Cleveland CSA:

[**]These 1,073 origin-destination pairs represent aerodrome pairs through which at least one passenger could save time by taking the UAM mode.

1) Cuyahoga County Airport (CGF) → Lansdowne Airport (O4G)
   - 15 minute mode transition/embarkation time and 10 disembarkation/mode transition time
   - 29.0 minute UAM flight duration
   - 44 passengers out of 1,367 potential passengers have a UAM-preferred trip
   - 11 daily flights
2) Galion Municipal Airport (GQQ) → Columbia Airport (4G8)
   - 15 minute mode transition/embarkation time and 10 disembarkation/mode transition time
   - 30.4 minute UAM flight duration
   - 40 passengers out of 1,446 potential passengers have a UAM-preferred trip
   - 10 daily flights

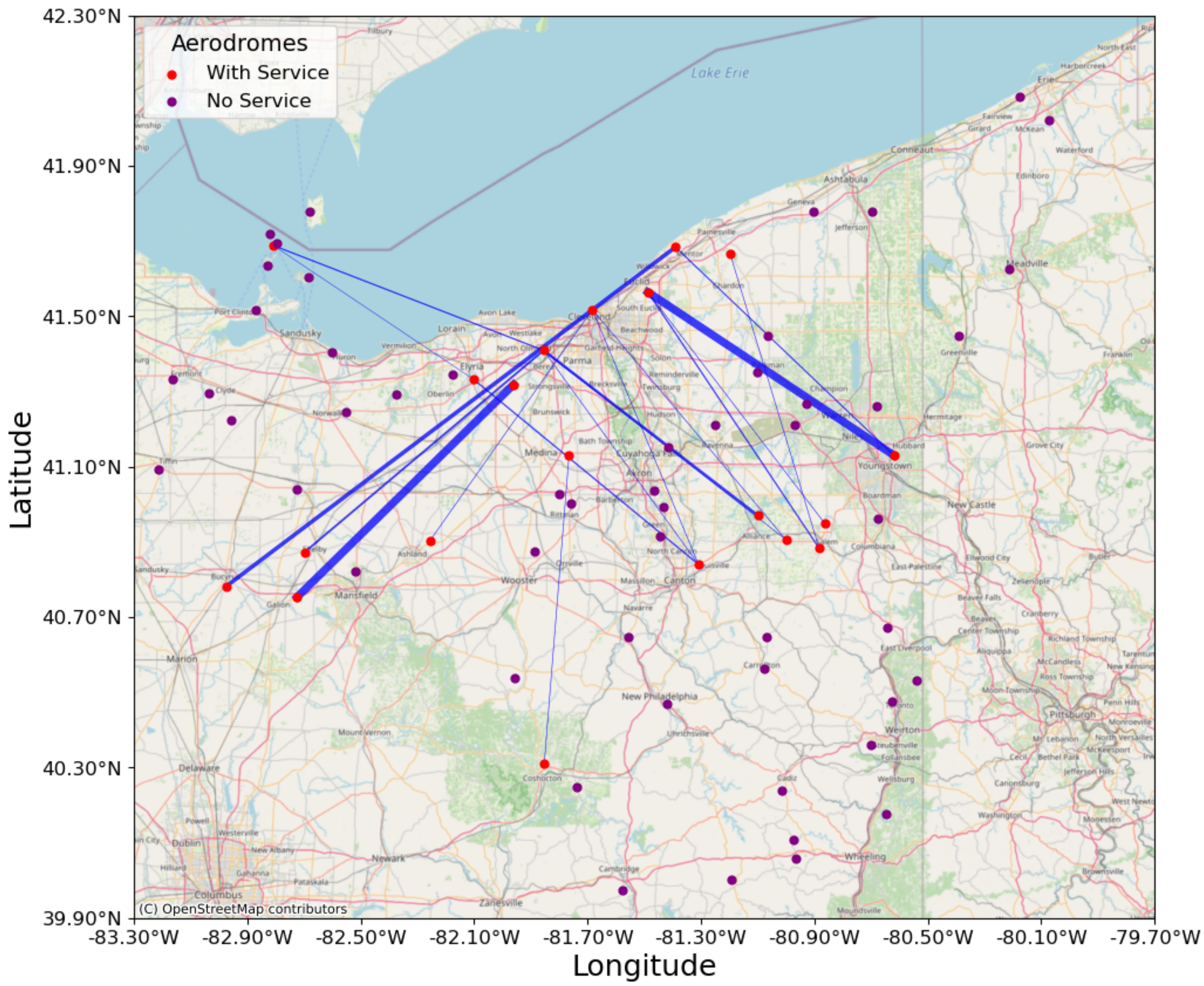


Fig. 5 Ridesharing-enabled UAM network for Cleveland. Aerodromes with UAM services are denoted by red dots. Unserved aerodromes are represented by purple dots. The linewidth is a measure of the number of flights between the two aerodromes, with a thicker line denoting more flights. (Background map data ©OpenStreetMap contributors. Background Map Data available under the Open Database License [38])

Finally, we see a total of 25 possible aerodrome pairs, encompassing 20 aerodromes to support UAM operations. This means that despite considering a total of 72 aerodromes, 47 of those do not have enough passenger demand to support UAM operations within the bounds of our assumptions. Cuyahoga County and Lansdowne airports would see the highest number of flights (15 and 14, respectively). We also observe that most aerodromes would have unbalanced arrival and departure rates that would necessitate a large number of repositioning flights.[††] The current cost estimates do not take into account these flights or repositioning costs, thus actual costs would likely be higher than the idealized case presented here.

V. Conclusions

This paper introduces the Passenger Aggregation Network with Very Efficient Listing (PANVEL) algorithm designed for examining the role of ridesharing in advancing Urban Air Mobility (UAM) operations. PANVEL is integrated with a computational framework that analyzes the mode choices of passengers within a metropolitan area for daily trips. The PANVEL algorithm estimates passenger-specific wait times based on their value of time and route to aggregate passengers into aircraft yielding high load factors. PANVEL is a lightweight algorithm that captures meaningful considerations regarding the economic attractiveness of ridesharing-enabled UAM trips for strategic analysis of particular metro areas.

A demonstration case study is conducted to explore the workings of PANVEL. Using the computational framework with the PANVEL algorithm activated, an increase in the number of passengers selecting the UAM option is estimated, mainly due to cost reductions per passenger resulting from ridesharing. The algorithm places emphasis on maximizing occupancy rates on board aircraft under the assumption that high load factors will ultimately lead to lower fares for passengers.

There are many assumptions currently in the PANVEL algorithm that make results presented in this paper primarily for demonstration purposes. At best, the results represent an “upper bound" on the benefits of ridesharing due to our unconstrained modeling and assumptions of perfect knowledge about various parameters that in reality would come with degrees of uncertainty. Ongoing and future work aims to refine these assumptions, develop improved estimates of UAM operating costs, and obtain more reliable assessments of ridesharing and its role in enabling substantial UAM operations.

VI. Acknowledgements

This research is supported by the National Aeronautics and Space Administration (NASA) through the Logistics Management Institute under contract number DATSS 80HQTR18A0013-80HQTR23F0116 (TO#70). The background map data in Fig. 5 is available under the Open Database License [38]. The last author was supported by the AAM Mission Integration Office, which is funded by the NASA Aeronautics Research Mission Directorate. The authors extend their gratitude to NASA’s Brandon Sells, Jim Murphy, and Yuri O. Gawdiak for their insightful feedback throughout this project.

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[††] Nominally these flights would not contain paying passengers, but it may be possible to offer sufficiently low fares that could make some travelers willing to pay something for flights. Analysis of such scenarios is beyond the scope of our existing modeling.

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