Refined Analysis of CO_2 Emissions in Urban Air Mobility Networks

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In this study, we examine the environmental impact of Urban Air Mobility (UAM) operations as measured via carbon dioxide (CO_2) emissions by leveraging a computational model from previous studies that has been refined and expanded. Several scenarios are examined in which total transportation emissions for a representative day in a metro area are distributed differently among vehicle types and transportation modes. Specifically, we investigate the use of electric air vehicles in a UAM network; the increasing presence of electric ground vehicles for ground transportation; the impacts from implementing ridesharing in UAM operations; and the effects of varying electricity grid emissions. Results for a case study in the Chicago, IL metro area indicate that incorporating electric ground vehicles and UAM ridesharing can both lead to reduced CO_2 emissions. These preliminary results indicate that carbon emissions from UAM operations leveraging ridesharing and all-electric aircraft may not pose a significant operational limit on UAM, though further improvements to the modeling are warranted.

I. Introduction

Advanced Air Mobility (AAM) is a relatively new approach to transportation that employs small, newer-generation aircraft for regular travel over local and intraregional distances [1]. Although there is not a consensus on the exact scope of AAM, most view passenger-carrying options in AAM as comprising two distinct services: urban air mobility (UAM) and regional air mobility (RAM). UAM primarily caters to air transportation within metropolitan areas with electric vertical takeoff and landing (eVTOL) aircraft. On the other hand, RAM focuses on intraregional air travel, typically utilizing conventional or short takeoff and landing (CTOL or STOL) aircraft to fly between existing airports.

Our focus in this paper is on UAM, a concept that has the potential to facilitate fast, long-distance journeys within large metro areas [2]. UAM is typically envisioned as a multimodal transportation system in which aircraft fly between dedicated aerodromes*; consequently, individuals must leverage some ground-based transportation mode to travel to and from these aerodromes to ultimately reach their intended destination. Efforts are underway to initiate commercial services within the UAM domain in larger US metros, such as Miami and New York City, with significant backing and interest from various stakeholders [3, 4]. Urban planners, aircraft manufacturers, research organizations (e.g., NASA), and other entities have made significant investments in this field [5].

UAM is a system of systems (SoS), meaning that there are multiple, independent entities involved with complex interactions across technology, operations, policy, and economic realms [6]. From this holistic SoS view, it remains difficult to determine in what circumstances, if any, UAM will have beneficial impact on overall emissions [7]. Past

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

studies have indicated emissions savings from eVTOLs relative to automobiles on a per-passenger-mile basis under certain assumptions† [8]; however, it is not clear if the net effect on emissions of implementing UAM within a given metro area will be positive or negative due to the complex interactions of the full transportation SoS. For example, it is possible that the total number of miles traveled per passenger could notably increase as UAM is implemented since aerodromes used to connect routes may be "out of the way" compared to traditional modes. Consideration of the full SoS is important to help determine if potential reductions in emissions can be realized in practice. Furthermore, electricity consumed by eVTOL aircraft operations may result in considerable upstream emissions, tying the environmental friendliness of these operations to the cleanliness of the electric grids from which they draw power [9]. Consequently, the environmental impact of UAM operations is closely linked to the specific metros where they are deployed. The desire for widespread adoption of UAM prompts the need for serious consideration of environmental impact through pre-deployment studies; noting that adverse impacts could potentially limit the deployment and scale of UAM operations [10].

Since UAM services will directly compete with ground transportation modes in the broader urban transportation SoS, environmental impacts from innovations in both air and ground modes must be examined in concert. The recent surge in sales of battery-electric ground vehicles (EVs) complicates the comparison of emissions between UAM and ground transportation modes [11]. A rise in both EV usage and UAM may challenge the capacity of the electric grid and potentially limit UAM operations, especially in terms of the number of eVTOLs that can be charged simultaneously [12]. Although the results in Ref. [12] do not identify a clear environmental impact on a metro due to EV implementation, they justify the need for an initial investigation into how EVs can impact UAM operations in other capacities, in this case, emissions.

Additionally, ridesharing in the UAM mode could significantly reduce per-passenger travel costs and emissions compared to non-ridesharing scenarios and thereby relax economic-based limits on UAM adoption [13, 14]. However, our previous work suggests that operational limits on UAM are specific to each metropolitan area, and ridesharing would likely be no different [15]. Furthermore, the differences in the carbon intensity of the electric grid between different metro areas necessitate the need for analysis of factors for each individual metro region.

This paper investigates CO_2 emissions for a metropolitan area UAM network and addresses two key research questions:

1) How do the increased incorporation of EVs and reductions in the metro electricity grid carbon intensity impact emissions within a multimodal transportation setting that includes a passenger UAM network?
2) How can we assess total emissions in the presence of ridesharing for the UAM mode and compare these emissions to the potential reductions from the adoption of EVs?

The remainder of the paper is organized as follows. Section II provides background information about our previous research that is heavily integrated into the work described in this paper. Section III describes the emissions calculation process for results that will be presented in the following section. Section IV presents a case study on Chicago and a metropolitan-wide comparison that provides modeled emissions results for various scenarios. Section V provides conclusions and outlines recommendations for future work.

II. Background and Previous Research

A. UAM Allocation Utilizing Travel Demand

The work we present in this paper builds directly on past work by several of the authors, which we will briefly describe in this subsection. Some of these previously conducted studies modeled and quantified factors that could inhibit large-scale AAM operations. Our analysis begins by generating trips—specifically, commuter trips performed over a single day within metropolitan areas—that serve as input data for in-depth operational limits analyses. This trip data is then processed through a computational framework that evaluates the *effective cost* of each mode of transportation for all trips [13]. The effective cost of a trip is the actual cost plus a perceived "cost" of the time spent traveling, which is the individual passenger's value of time (VoT) multiplied by the amount of time spent traveling [16].

We assume that all travelers in the system are assigned the mode of travel with the least overall effective cost for them; this follows an assumption that all of the travelers are "economically rational actors." Though this assumption does not reflect true traveler behavior, the simplification allows us to streamline the decision logic in our modeling. The computational framework assigns a mode preference to each trip (i.e., a *car mode* trip involving only ground

† most notably high aircraft load factors over relatively long distances for everyday travel

transportation or a *UAM mode* trip that contains a UAM flight segment) and provides a series of outputs that allow for further analyses, such as emissions. If a trip is assigned the UAM mode based on the effective cost, it is termed a *UAM-preferred trip*. Previous investigations on the impacts of aerodrome throughput [15], emissions [7], and weather [17] on UAM operations utilize the same computational framework and analysis process shown in Fig. 1.

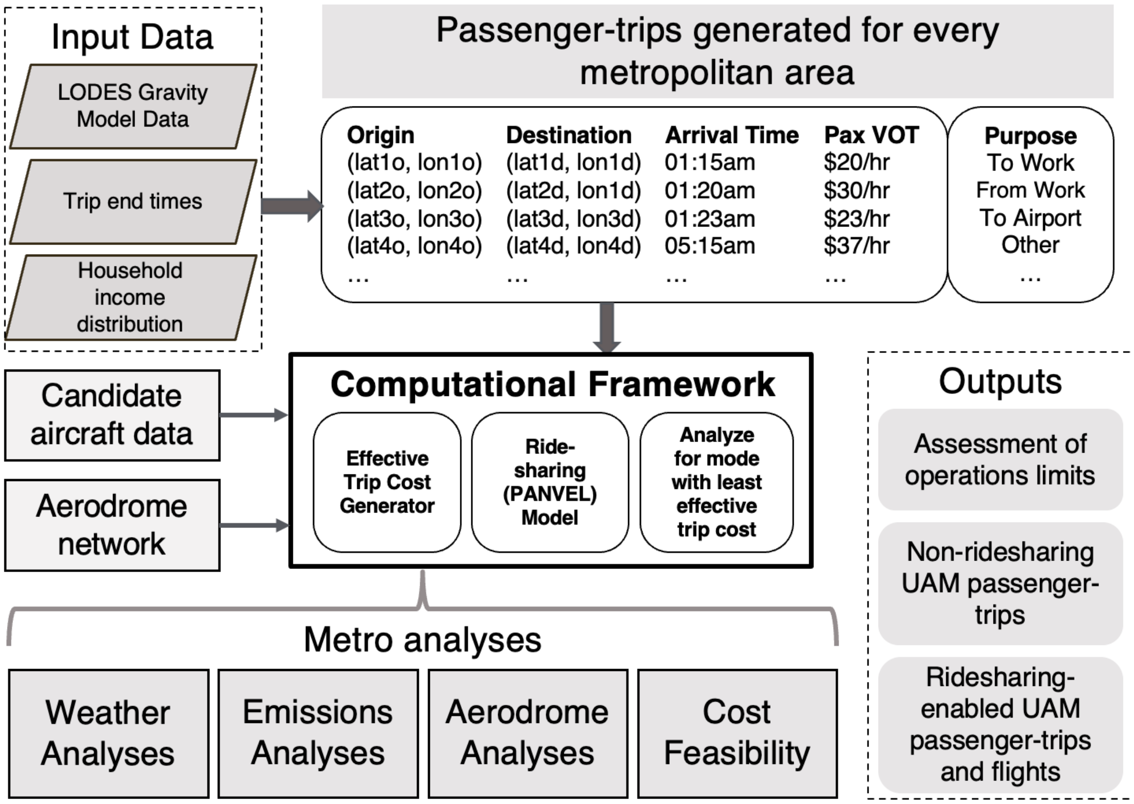

Fig. 1 Overview of the complete analysis process for AAM operational limits, including an enhanced computational framework with the PANVEL ridesharing model [18] for analyzing trips within metros, plus additional analysis modules.

The computational framework begins by taking three key inputs, one of which is an aerodrome network dataset specific to a given metro area. This first dataset identifies all existing locations for UAM infrastructure, obtained from the Federal Aviation Administration (FAA) National Flight Data Center database [19]. Analyses have been performed with the computational framework using aerodrome networks of varying sizes, such as three-aerodrome and ten-aerodrome networks, in addition to the full aerodrome network for every metro [15]. The full aerodrome network contains all public-use aerodromes (as of 2021) within defined combined statistical area (CSA) boundaries corresponding to the metros being studied, plus a 12.4 mile (20 km) buffer zone outside the boundary [‡]. Three-aerodrome and ten-aerodrome networks contain aerodromes selected based on their characteristics and metro area features, such as geographic location and surrounding population densities and income levels [15]. The 70-aerodrome network visualized in Fig. 2 depicts the locations of all of the public-use infrastructure deemed by the authors as possible locations for aerodrome operations in the Chicago metro area.

The second key input to the computational framework is a trip dataset describing all of the commuter trips taken in a representative day for the given metropolitan area. This begins with using the trips listed in the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employee Statistics (LODES) [21] data from the US national census. These trips in LODES do not contain any information about the time of the trip, so we utilize the distribution of times of day for commuter trips from the National Household Travel Survey (NHTS); a random time sampled from this distribution is assumed to be the arrival time for each trip. Additionally, we assign the Value of Time (VoT) of individuals to the trips in LODES based on the home location of the trip, and by assuming that an individual's

[‡]This buffer zone is included so that aerodromes close to all potential trip origins or destinations within the CSA are included.

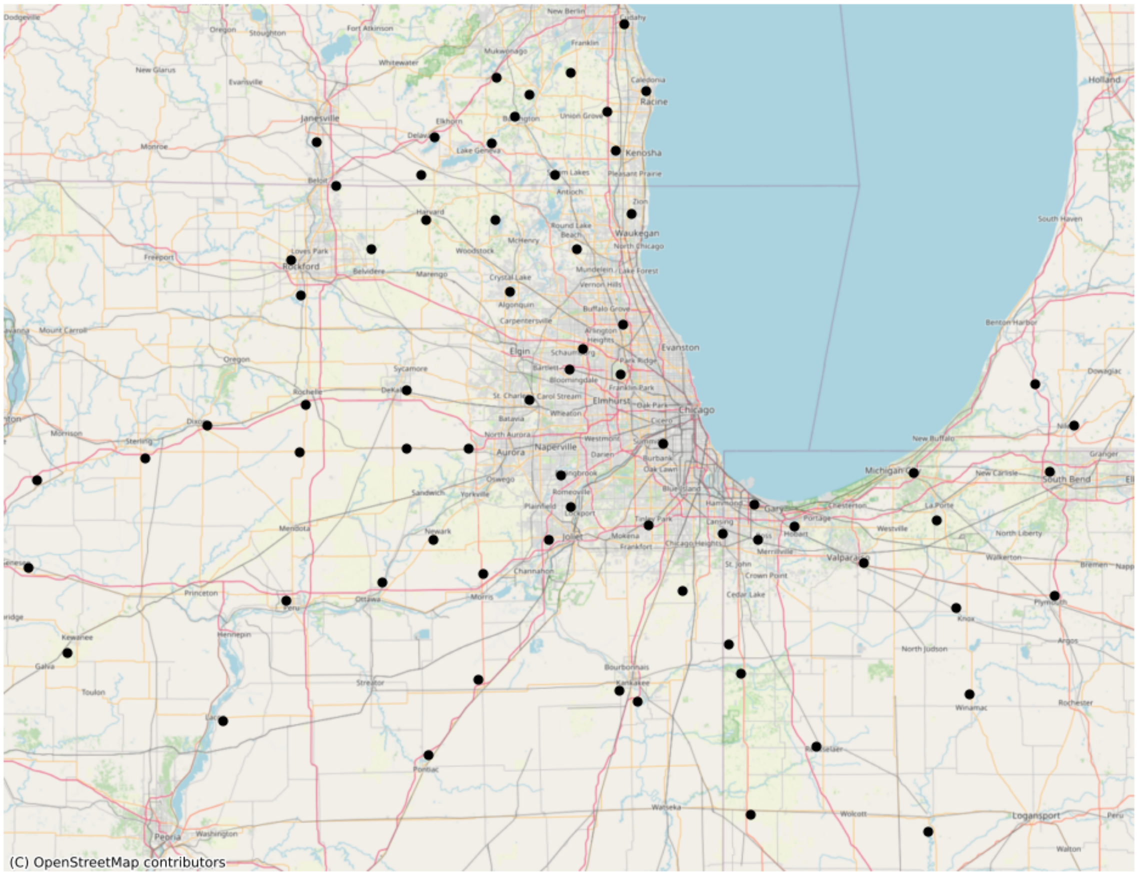

Fig. 2 Chicago full 70-aerodrome network. All aerodromes on this network are public use. Background map data © OpenStreetMap contributors. Data available under the Open Database License [20]

value of travel time equals their hourly income. We recognize that different circumstances for a specific trip may cause an individual's value of travel time to change; however, the assumption that travel time equals hourly income allowed sampling from the American Community Survey (ACS) [22] to assign a commuter's value of travel time to a trip based on their respective home location instead of using random assignments [15].

The third input to the computational framework is a list of parameters that define the notional UAM eVTOL aircraft using in this study. This is the same aircraft used in prior studies [14, 15]. Specific aircraft parameters include a nonstop range of 50 nautical miles, a maximum passenger capacity of four, and a direct operating cost rate of $605 per hour based on estimates from Uber Elevate. [23–25]. A detailed set of characteristics for the notional eVTOL aircraft is presented in Table 2 in Appendix A.

After generating the aerodrome network dataset and the commuting trip dataset, which now contains the origin and destination of the trip, the trip arrival time, and the commuter's VoT, the computational framework takes these datasets as inputs and estimates the distance, duration of travel, operating cost, and the total effective cost associated with all trips in the trip dataset for two modes of travel with mission profiles shown in Fig. 3. The first mode, known as the car mode, entails a traveler using only ground transport to complete their entire trip (A → B in Fig. 3). The second mode, known as the UAM mode, involves a traveler taking ground transport to their departure aerodrome, taking a UAM flight to their arrival aerodrome, and taking ground transport to their final destination (A → C/G/J → E/I/K → B in Fig. 3). For some trips, the ground distance from the origin to the departure aerodrome plus the ground distance from the arrival aerodrome to the destination exceeds the ground distance from the trip origin point to the destination point. We assume these trips would see no time benefit from including the UAM segment, so the computational framework does not consider assigning these trips to the UAM mode. For trips where the UAM flight holds the potential to reduce the travel distance (i.e., not cause backtracks), the computational framework computes the effective cost for a car mode trip and the effective cost for the UAM mode trip based on the transportation costs and the VoT of each traveler. The trip mode with the lowest effective cost is the mode assigned to that trip.

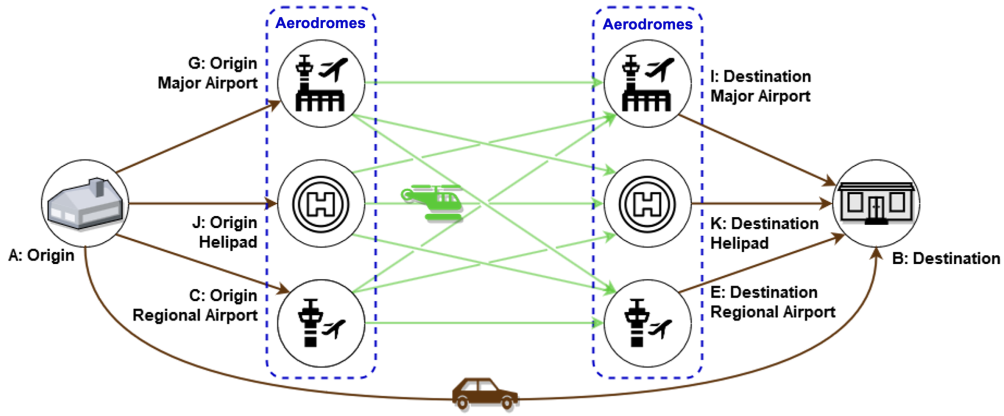

Fig. 3 Network model of travel mode options within the computational framework: A → B for the car mode and A → C/G/J → E/I/K → B for the UAM mode.

The authors encourage readers to refer to Refs. [13–15, 24–27] for a chronological understanding and a more detailed description of the development of the computational framework, including the processes for trip generation and the selection or siting of existing infrastructure for various aerodrome networks.

B. Relevant Work on Emissions Modeling

In the past, our team has extensively utilized the computational framework to perform analysis on various UAM operational limits. This includes studies into modeling CO_2 emissions from both UAM operations and ground-based trips. A study by Mudumba et al. [7] models and compares CO_2 emissions from the UAM mode with those from automobile-only trips for a set of given origin-to-destination trips within the Chicago and Dallas metropolitan areas. The Mudumba et al. study [7] serves as a solid foundation on which the current emissions study seeks to build. Figure 4 shows the flow of analysis for estimating CO_2 emissions for both transport modes.

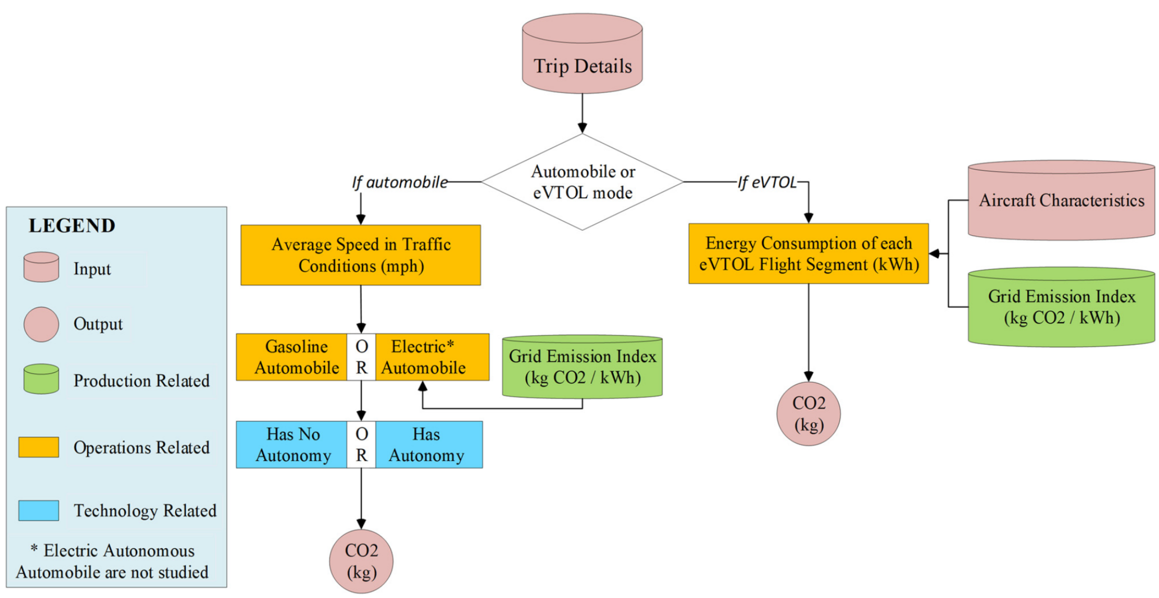

Fig. 4 Emissions modeling process that provides final carbon dioxide emissions values (in kilograms) [7].

The Mudumba et al. study provides an in-depth discussion of eVTOL aircraft sizing and parameters to calculate the energy required for a given flight. They also consider the grid emission index, EI_{GRID}, that defines the amount of CO_2 produced per unit of energy generated, typically expressed in units of kilograms per kilowatt-hour (kg/kWh), by an electric grid that serves a given metro area. In the Mudumba et al. study, different ground vehicle modes with internal combustion engine (ICE) cars and EV cars were considered with and without autonomy. The study also acknowledges that the production of batteries used in EV cars and eVTOL aircraft also contributes to CO_2 emissions but omits analyses on these due to uncertainties in production processes. The Mudumba et al. study demonstrates that ground conditions (e.g., driving distance and speed) can determine whether a trip containing a UAM segment may contribute less towards CO_2 emissions [7].

C. Background on the Grid Emissions Index

The emissions associated with UAM operations within a metro area are closely linked to its respective local electricity grid [7]. The cleaner the electricity grid (i.e., the more the grid predominantly comprises renewable or nuclear sources), the lower the emissions generated. To measure this, we utilize EI_{GRID} values sourced from the Environmental Protection Agency (EPA) eGRID Power Profiler [28], which quantifies the cleanliness of the electric grids across different metro areas according to their source composition. The EPA eGRID regions are noted from the North American Electric Reliability Corporation (NERC) subregions. This index varies across different metro areas based on the eGRID subregion in which it is placed. Although the Mudumba et al. study [7] utilized 2020 Energy Information Administration (EIA) Outlook data, all comparisons performed in this paper utilize the most recent 2022 data from the EPA. Figure 5 demonstrates a considerable change in emissions grid index values within a span of two years, highlighting the need for updated analysis.

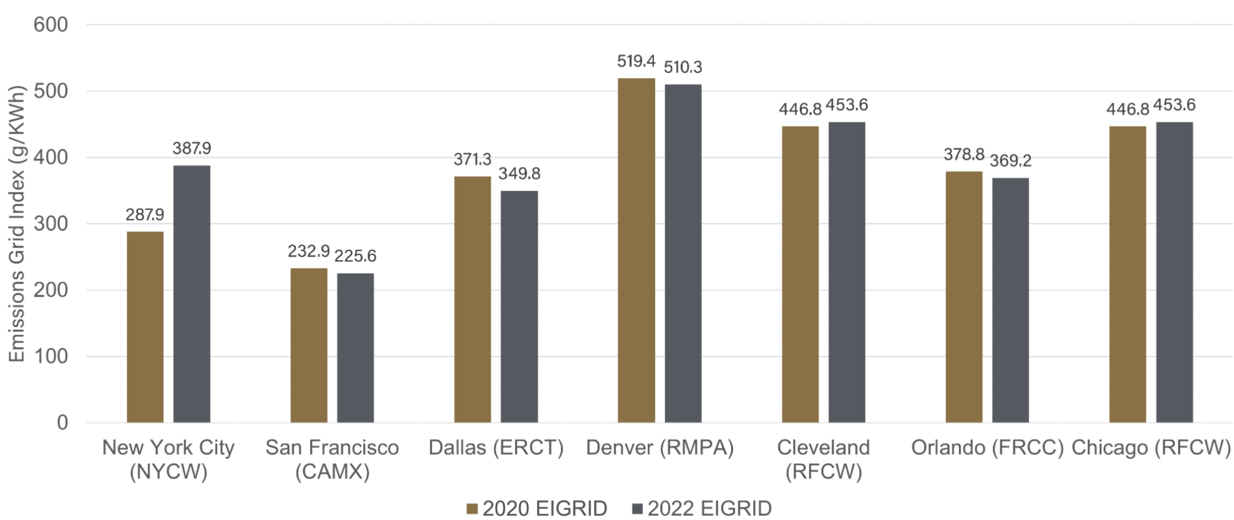

Fig. 5 EI_{GRID} values vary in a short span of two years due to the changes in sources of energy in each region. We show a comparison between grid emissions index values between 2020 and 2022 for previously investigated metros. All EI_{GRID} values represented here have been obtained from the EPA [28].

D. Related Work on Ridesharing Models

Results from our prior research indicate that in some metro areas, particularly those reliant on carbon-intensive electricity grids, a UAM trip might produce higher carbon emissions compared to an equivalent ground-based trip [7]. Such instances underscore the necessity of ridesharing to render UAM environmentally viable in addition to increasing affordability for travelers. Given the nascent stage of UAM technology, integrating compatible ridesharing models into its deployment is necessary for broad ridership due to the anticipated high operating costs of eVTOL aircraft [23]. Ridesharing shows promise in reducing overall emissions, because a single UAM aircraft with multiple, ridesharing passengers can replace multiple single-occupant cars on the road. This paper employs a ridesharing model termed PANVEL [18] integrated into the computational framework described above to examine the impacts of ridesharing on emissions within a metro area. The PANVEL model is an aggregation algorithm that groups passengers traveling between identical pairs of departure and arrival aerodromes. It takes into account each passenger's specific VoT, car costs, UAM costs, aerodrome arrival time, and waiting time to allocate passengers to ridesharing UAM trips. The PANVEL model involves two loops that assess trip rideshare compatibility based on time and cost. Time compatibility ensures that each passenger arrives at the departure aerodrome within the maximum waiting time acceptable to other passengers. Cost compatibility checks if the effective trip cost is lower than that of a purely ground-based trip; this cost compatibility accounts for the additional trip time associated with gathering other passengers for the flight. If both conditions are satisfied, the trip is classified as a UAM-preferred trip. The aim of this algorithm is to maximize the total number of UAM-preferred trips. The authors suggest readers to refer to Ref. [18] for a more detailed understanding of the PANVEL model.

III. Methodology

This work utilizes trips modeled from the computational framework described in Section II, allocates travelers' mode choices based on the least effective cost and outputs the network-wide daily emissions over a range of scenarios. In order to investigate the impact of varying levels of EV adoption on total CO_2 emissions, we vary the EV adoption rate, which we refer to as the *EV utilization rate*, between 7% and 100%. The EV utilization rate describes the proportion of EVs relative to all cars on the road and is distinct from the EV market share which describes the proportion of EV sales relative to sales of all cars. Because we are considering possible future states with the implementation of UAM, we must project how EV utilization rates will vary into the future. Noting that the market share of US EV sales in 2022 is 7% according to the Congressional Budget Office (CBO) and assuming that the EV proportion of all cars on the road will continue to rise gradually due to a general increase in the EV market share as projected by the CBO [29], we chose an EV utilization rate baseline of 7% for our modeling. This baseline corresponds to a likely future scenario when EVs will make up 7% of all cars on the road, and we will also consider higher EV utilization rates in our modeling.

We compare emission results among cases of no-UAM, UAM without ridesharing, and UAM with ridesharing. Finally, we also investigate how emissions from each vehicle type and travel mode vary with changes in electricity grid emissions index values. In this paper we address the Chicago, IL metropolitan area; we expect to report results for several other metros in future publications. We detail the full emissions modeling process below, along with the various assumptions, inputs, and experiment choices used in this CO_2 emissions study.

A. Travel Modes Considered

Figure 6 provides an overview of the two travel modes – the car mode and the UAM mode – analyzed in the computational framework, along with the vehicles assigned to each segment on these modes. The car mode involves a single segment from an individual's origin to their destination performed by private ground transportation, using either an ICE vehicle or an EV. The UAM mode involves an initial ground segment from an individual's origin to their departure aerodrome, a UAM flight segment to their arrival aerodrome, and a last-mile ground segment from the individual's arrival aerodrome to their destination. The two ground segments in the UAM mode are also performed by either an ICE vehicle or an EV in our modeling. The EV utilization rate input parameter determines the fraction of ground segments assigned an ICE vehicle or an EV, where a 100% EV utilization rate assigns all ground segments to EVs. The approach to assigning ground segments to EVs is described in further detail below in Subsection III.C.

Ground vehicle characteristics have been kept consistent with prior emissions analysis work [7]. This includes a ground vehicle average speed for both ICE vehicles and EVs of 35.2 miles per hour. Furthermore, the ICE vehicle is characterized by a fuel efficiency of 32 miles per gallon and a set emissions rate of 8.1 kg of CO_2 per gallon of fuel. All ground vehicle segments are also assumed to be single-passenger trips. The UAM aircraft modeled in the travel network is an eVTOL with characteristics defined in Table 2 of Appendix A.

B. Investigating Projected Electric Vehicle Usage

Because large-scale UAM will not be implemented for several years and the EV adoption rate across the US is gradually increasing, there is uncertainty around what level of EV adoption can be expected when UAM operations begin to be implemented. To investigate how differing EV adoption rates may impact network-wide emission across car and UAM transportation modes, we perform a sweep of EV utilization rates between 7% and 100%, reflected in various travel network scenarios presented in Section IV. Although changes in EV adoption rates do not affect emissions generated from UAM flights themselves, we are mindful of the changes in emissions generated by car segments to and

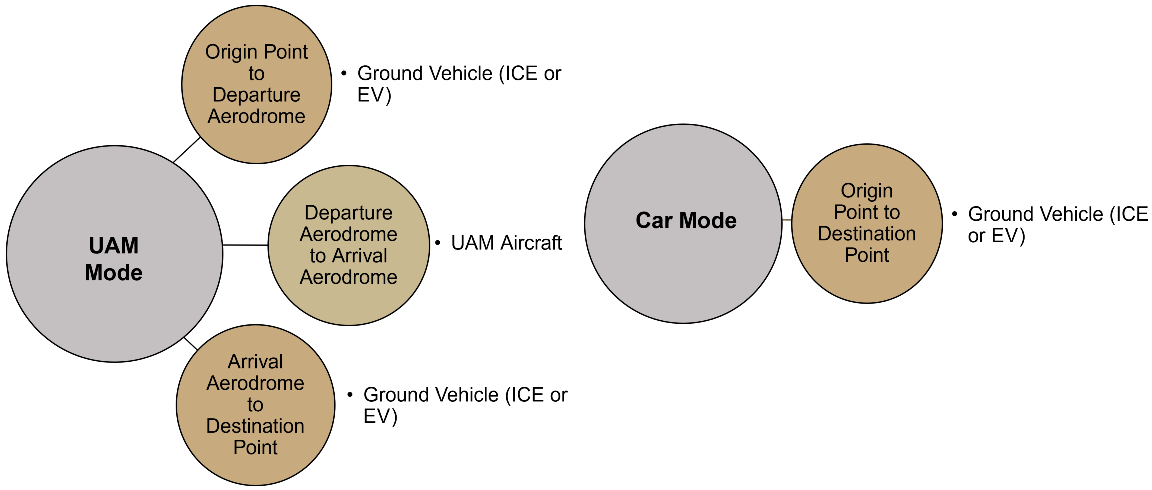

Fig. 6 A breakdown of the various trip segments and vehicles utilized for the two modes of travel considered in the computational framework: the car mode and the UAM mode. Both modes involve at least a single ground segment, and whether a ground segment is assigned an ICE vehicle or an EV depends on the EV utilization rate.

from aerodromes in the UAM mode, which may impact the sustainability of UAM operations. As such, some of these car segments to and from aerodromes may be served using EVs depending on the EV utilization rate, and thus, the EV utilization rate will affect total UAM mode emissions.

Changes in the grid emissions index, EI_{GRID}, will only cause changes in emissions generated by EV cars and eVTOL aircraft due to their direct reliance on the electric grid for battery recharging. The EI_{GRID} has no direct impact on ICE vehicle emissions generated during trips. Each year, the EI_{GRID} corresponding to a given metro area will likely fluctuate as the energy source composition changes continuously, as evidenced from Fig. 5. As mentioned in Section II, the EIA has projected detailed year-on-year variations in electric power source emissions in the US based on many factors, including economic growth. For our modeling in which we desire to understand the general impacts of the electricity grid emissions on net transportation CO_2 emissions, we baseline our analysis in the 2022 EI_{GRID} value and vary this parameter based on general trends suggested by the EIA. Specifically, the EIA projects a 2.8% annual reduction in electric power emissions beyond 2022, equivalent to a nearly 55% reduction in the EI_{GRID} value by 2050 [30].

In addition to general projections into the future, we are also interested in studying what a reasonable "lower bound" on the emissions from the electric grid could be and how this would impact transportation CO_2 emissions. The Intergovernmental Panel on Climate Change (IPCC) has put forth an emissions breakdown of energy sources used in electricity generation in its most recent Assessment Report, where it was stated that onshore wind power results in the lowest emissions among all sources of power at 0.011 kg/kWh [31]. Therefore, for the purposes of this study, we make an extremely idealistic assumption of the lowest possible EI for electric generation by choosing an EI_{GRID} value of 0.011 kg/kWh. We make this assumption mindful of a) the difficulties of predicting future electric grid compositions and b) the fact that a region's grid will likely never be fed by only one renewable source or even fully by renewable sources indefinitely.

Table 1 lists the present, projected, and idealized EI_{GRID} scenario values; percent reductions from the present baseline; and source reference. These three EI_{GRID} values are used in multiple analyses outlined in Section IV as variations of the Chicago metro area EI_{GRID} value, and it is important to note that they are not tied to any specific year when applying analysis.

Table 1 Variations of Chicago-area EI_{GRID}, their specific values, and their reduction from present value

Name	Value (kg CO_2/kWh)	% Reduction from Present	Source
EI_{GRID} Present	0.4749	0	EPA 2022 Region Data [28]
EI_{GRID} Projected	0.2144	55	EIA Annual Projected 2.8% Reduction till 2050 [30]
EI_{GRID} Idealized	0.011	98	IPCC Wind Power Emissions [31]

C. Calculating Aggregated Emissions for Metro Areas

For each trip modeled in the computational framework, we assign a mode preference based on the effective cost metric. We calculate trip-wise emissions according to the vehicle types involved for each mode. Denoting the total number of daily commuter trips in a metro area as N, we denote the number of UAM-preferred trips, and therefore the total number of UAM segments, as N_{UAM}. Likewise, the number of car-preferred trips is denoted as N_{car}. For a trip performed on the UAM mode, we calculate the emissions generated from the UAM flight segment, denoted as $E_{\text{trip,UAM}}$, separately from the emissions generated from the combined ground segments to/from aerodromes, denoted as $E_{\text{ADtrip,ICE}}$ if taken via an ICE car or $E_{\text{ADtrip,EV}}$ if completed in an EV car. A trip assigned to the car mode entails only emissions calculated on the origin-to-destination car segment, denoted as $E_{\text{trip,ICE}}$ if utilizing an ICE car or $E_{\text{trip,EV}}$ if the trip is taken via an EV car. The aggregation process for these different types of emissions will be described in further detail below.

To calculate the emissions from varying numbers of EVs on the road, we determine the number of trips that will leverage EVs, N_{EV}, by multiplying the EV utilization rate, U_{EV}, by the number of total trips identified from the trip dataset and rounding to the nearest whole number. We ensure the same relative number of trips via the car mode or UAM mode utilize EV cars by considering the UAM-preferred trips and the car-preferred trip sets separately. We determine the number of car mode trips that will leverage EV cars for ground segments, $N_{\text{EV,car}}$, by multiplying U_{EV} by the number of car-preferred trips and rounding the result to the nearest whole number. Then, we determine the number of UAM mode ground segments that will be taken via an EV car, $N_{\text{EV,UAM}}$, by subtracting the number of car mode trips that leverage EV cars from the total number of trips with EVs, $N_{\text{EV,UAM}} = N_{\text{EV}} - N_{\text{EV,car}}$. To determine which specific car mode trips will leverage EVs, trips are considered sequentially in the order they are identified by the computational framework. Because this order follows the order of trips in the LODES dataset, without any specific grouping or ordering, this is equivalent to selecting $N_{\text{EV,car}}$ trips randomly. We obtain the number of car mode trips leveraging ICE cars, $N_{\text{ICE,car}}$ by subtracting the total number of car-preferred trips with the number of car mode trips leveraging EV cars, $N_{\text{ICE,car}} = N_{\text{car}} - N_{\text{EV,car}}$. Finally, obtain the number of UAM mode ground segments that will be taken via an ICE car, $N_{\text{ICE,UAM}}$, by subtracting the number of UAM mode ground segments that will be taken via an EV car from the number of UAM-preferred trips, $N_{\text{ICE,UAM}} = N_{\text{UAM}} - N_{\text{EV,UAM}}$.

To investigate the impact of UAM ridesharing[§] on total daily network-wide emissions, we leverage a UAM ridesharing trip dataset from the PANVEL ridesharing model [18] as input. Because the PANVEL algorithm does aggregate trips into groups of trips where the commuters have the same destination-arrival aerodrome pairs and compatible trip times, the approach to determine which UAM mode trips employ EV cars for the ground segment uses an approach to randomly choose $N_{\text{EV,UAM}}$ trips from the list of all of the UAM-preferred trips, so that these trips are also randomly selected. The total emissions are determined in the same manner as above, except that emissions produced per UAM flight, $E_{\text{trip,UAM}}$, are calculated per aircraft trip rather than per passenger trip.

Emissions for each vehicle type are calculated following the work of Ref. [7]. Specifically, Mudumba et al. provide a fourth-order polynomial for calculating the energy required per mile for an EV as a function of the average ground speed; multiplying this energy consumed per mile by the grid emission index gives the CO_2 emissions per mile, and the total emissions are then determined from the number of miles traveled by EV. The ICE vehicle emissions similarly depend on the average ground speed and are calculated based on a function Mudumba et al. modified from Barth and Boriboonsomsin [32] as described in Ref. [7]. Finally, the UAM flight emissions are determined by breaking the flight into hover, climb, cruise, and descent segments; determining the energy required for each of these segments based on the time spent in the segments; adding the energy required for all segments together to determine the total energy required for flight; and finally multiplying the energy required for flight by the grid emissions index.

Overall, we consider five types of travel segments in our emissions aggregation process:

1) a ground segment in the car mode performed by an ICE car whose emissions are denoted by $E_{\text{trip,ICE}}$
2) a ground segment in the car mode performed by an EV car whose emissions are denoted by $E_{\text{trip,EV}}$
3) a flight segment in the UAM mode performed by an eVTOL aircraft whose emissions are denoted by $E_{\text{trip,UAM}}$
4) combined ground segments to and from aerodromes in the UAM mode performed by an ICE car whose emissions are denoted by $E_{\text{ADtrip,ICE}}$
5) combined ground segments to and from aerodromes in the UAM mode performed by an EV car whose emissions are denoted by $E_{\text{ADtrip,EV}}$.

[§]It should be noted that ridesharing is not considered for first- and last-mile passenger journeys, which are fulfilled on individual car segments.

Each of these emissions variables correspond to a singular segment (or combined ground segments in the UAM mode) within a single trip. We perform a summation of each of these emissions variables over all the trips in the travel network to obtain the emissions totals for each type of travel segment.

To better understand aggregate emissions results, we implement two different methods of subdividing the total emissions: by travel mode or by vehicle type. These methods are outlined below.

1. Defining Emissions by Mode of Travel

Analyzing emissions based on the trip mode involves aggregating emissions from all trips assigned to a particular mode irrespective of whether ground segments were assigned to an ICE car or an EV car. Our calculations for the "Car Mode Emissions" and "UAM Mode Emissions" aggregate values are shown in Eq. (1) and Eq. (2), respectively.

$$E_{\text{mode,car}} = \sum_{i=1}^{N_{\text{EV,car}}} E_{\text{trip,EV},i} + \sum_{j=1}^{N_{\text{ICE,car}}} E_{\text{trip,ICE},j} \tag{1}$$

$$E_{\text{mode,UAM}} = \sum_{i=1}^{N_{\text{UAM}}} E_{\text{trip,UAM},i} + \sum_{j=1}^{N_{\text{EV,UAM}}} E_{\text{ADtrip,EV},j} + \sum_{k=1}^{N_{\text{ICE,UAM}}} E_{\text{ADtrip,ICE},k} \tag{2}$$

This method of calculating emissions is used in cases where mode-by-mode comparisons are desired and the specific vehicle type is not significant. For example, integrating EVs into the ground network involves both the ground segments in the UAM mode as well as all car mode segments. In this case, it is useful to view the changes in emissions in both the UAM mode and the car mode to gather a system-level understanding of the environmental impact of EV integration into a travel network that also involves UAM.

2. Defining Emissions by Vehicle Type

An "emissions by vehicle type" analysis refers to a calculation method in which all emissions are separated by the vehicle type. In our analysis, this provides emissions for ICE cars, EV cars, and eVTOL aircraft separately. For instance, if a trip was identified as a UAM-preferred trip, the emissions generated from each segment of the trip are calculated and added to their own vehicle emissions aggregate value. This means that the emissions generated from the ground segments within the UAM mode would fall under either ICE car emissions or EV car emissions, depending on the EV utilization rate.

This method of calculation is helpful in cases where changes in the number of vehicles for each type may have a significant impact on the total emissions, and separating emissions by vehicle type can provide supporting evidence. For example, when enabling UAM ridesharing to the baseline, there are significant changes in the number of total UAM trips that are now being taken, and thus the number of UAM flights. Even though passengers may be pooled together on UAM trips, the ground segments of their UAM mode trips remain individual trip segments. In this case, it would be helpful to view changes in emissions when ridesharing is applied by vehicle because the emissions from each vehicle type is identified separately to illustrate the impact.

Equations (3), (4), and (5) illustrate the calculations involved to obtain aggregate emissions values for each vehicle type.

$$E_{\text{type,EV}} = \sum_{i=1}^{N_{\text{EV,car}}} E_{\text{trip,EV},i} + \sum_{j=1}^{N_{\text{EV,UAM}}} E_{\text{ADtrip,EV},j} \tag{3}$$

$$E_{\text{type,ICE}} = \sum_{i=1}^{N_{\text{ICE,car}}} E_{\text{trip,ICE},i} + \sum_{j=1}^{N_{\text{ICE,UAM}}} E_{\text{ADtrip,ICE},j} \tag{4}$$

$$E_{\text{type,UAM}} = \sum_{i=1}^{N_{\text{UAM}}} E_{\text{trip,UAM},i} \tag{5}$$

IV. Results: Chicago Full Aerodrome Network Case Study

We performed a case study on the emissions generated from passenger trips within the Chicago metropolitan area using a full 70-aerodrome network for UAM services. This case study follows the assumptions and methods discussed in the preceding sections and helps illustrate the impacts of EV adoption rates, changing electricity grid emission index values, and UAM ridesharing on net transportation emissions for daily trips in a metropolitan area.

Our representative Chicago travel network contains a total of 8,627,698 daily commute trips. The "baseline" scenario assumes no UAM service, thereby relegating these trips to be performed with ground (ICE and electric) vehicles. When UAM without any ridesharing is introduced, 2,907 of these trips become UAM-preferred based on the effective cost metric used in the computational framework and hence are assigned the UAM mode (which also involves car segments to and from aerodromes). The remaining 8,624,791 trips are modeled to remain served fully by ground vehicles.

Enabling UAM ridesharing (via the methods described in Ref. [18]) increases the number of UAM-preferred trips, or UAM-preferring passengers, to 154,093, due to significant effective cost reductions as modeled in PANVEL increasing UAM affordability to a larger swath of passengers. These 154,093 passengers are carried on a total 38,996 UAM flights in our modeling. Further insights on the impacts of enabling ridesharing on UAM, especially in the Chicago metro area, are expected in a future publication. It should be noted that these UAM-preferring passenger figures with and without UAM ridesharing do not account for a number of real-world factors that will place significant constraints on UAM operations, such as aerodrome throughput, aircraft and gate availability, and the weather.

The analyses presented below investigate changes in the estimated total daily network-wide emissions from varying EV utilization rates and grid emissions index values, and accounting for different UAM scenarios. We also investigate how enabling UAM ridesharing results in reduced per-passenger emissions compared to equivalent trips performed fully by single-passenger ground segments. Finally, we consider seven different hypothetical scenarios of different degrees of UAM implementation and EV integration into the travel network.

A. Varying Electric Vehicle Utilization Rates

Figure 7 presents a parameter sweep as electric vehicles are increasingly integrated into the ground network. We apply this sweep on cases with no UAM, with only single-passenger UAM flights, and then with ridesharing applied on the UAM network, following the methods described in Section III.

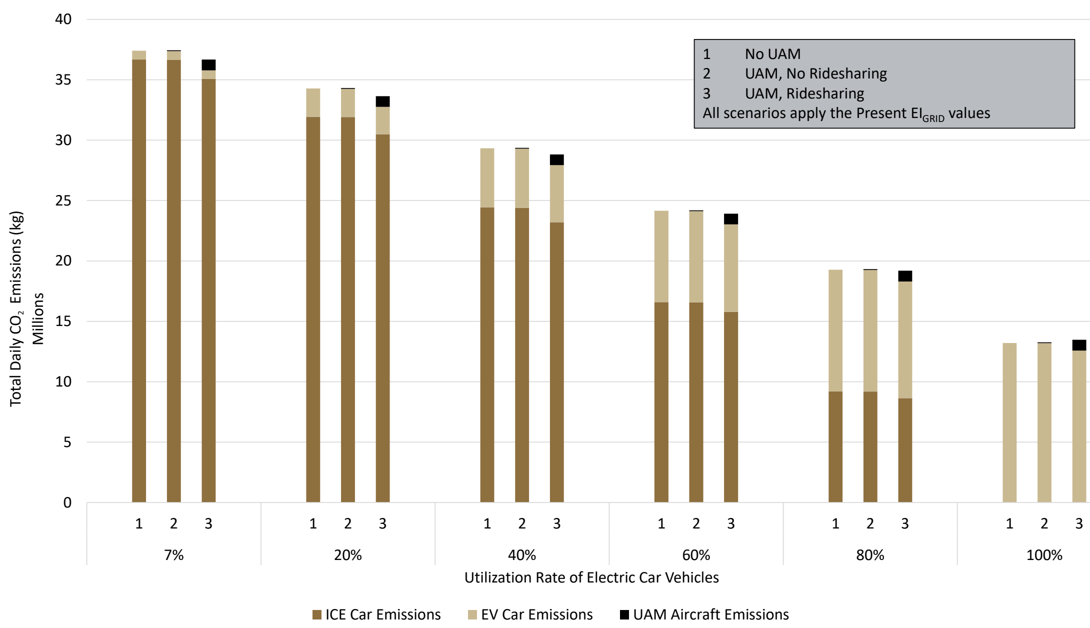

Fig. 7 Impact of EV usage on total emissions for passenger trips in the Chicago metro area (full 70-aerodrome network) assuming 2022 EI_{GRID} values across various UAM scenarios: no UAM, UAM without ridesharing, and UAM with ridesharing. A clear emissions reduction trend emerges with increasing EV utilization rate. Introducing UAM without ridesharing results in slightly increased emissions, whereas enabling UAM ridesharing causes decreases in total emissions across all scenarios shown except that of 100% EV utilization.

Figure 7 demonstrates a clear trend of consistent decreases in total network-wide emissions across all scenarios as the EV utilization rate is increased from its 7% baseline to a theoretical maximum of 100%.

Note that, across these different analysis scenarios, we estimate that an ICE vehicle trip generates between 3.2 and 3.7 times more emissions than an equivalent EV trip in our modeling. Meanwhile, the International Energy Agency (IEA) estimates that an ICE vehicle generates approximately 3.1 times more emissions than an EV over the course of their operational lifetimes (excluding emissions from manufacturing and production) [33]. Assuming that our emissions ratio between EV and ICE vehicles for equivalent trips can be extended over their operational lifecycles, our results for EV emissions may be slightly optimistic.

Compared to a non-UAM scenario (Scenario 1), introducing non-ridesharing UAM operations (Scenario 2) results in a slight increase in total network-wide emissions, with similar trends observed across all modeled EV utilization rates. The small nature of these emissions increases can be attributed to just 0.034% of all trips switching from a fully ground-based trip to one that involves a UAM flight segment. This emissions increase is most pronounced at a 100% EV utilization rate, where shifting from Scenario 1 to Scenario 2 decreases ground vehicle (EV) emissions by 12,353 kg but introduces UAM flight emissions of 70,935 kg. Altogether, the introduction of non-ridesharing UAM operations was found to cause a 0.44% increase in total network-wide emissions assuming a 100% EV utilization rate. In comparison, at a 7% EV utilization rate where the emissions increase from Scenario 1 to Scenario 2 is least pronounced, the introduction of non-ridesharing UAM operations was found to result in a 0.09% increase in total emissions.

On the other hand, enabling ridesharing in UAM (Scenario 3) does not result in a single clear trend for total emissions. For all EV utilization rates shown in Fig. 7 other than 100%, the total network-wide emissions are lowest for Scenario 3. Because practical EV adoption rates are generally anticipated to be at or below 80% through mid-century [29], these results indicate that UAM with ridesharing has the potential to provide a net CO_2 emission reduction for expected EV adoption rates. At a 7% EV utilization rate where net emission reduction effects are most pronounced, shifting from Scenario 2 to Scenario 3 results in a 2.06% decrease in total network-wide emissions.

However, at a 100% EV utilization rate, total transportation emissions are slightly increased in Scenario 3 (including UAM with ridesharing) relative to the no-UAM scenario (Scenario 1). Introducing ridesharing-enabled UAM operations to a non-UAM scenario results in a 2.02% increase in total emissions. Interestingly, enabling ridesharing in UAM also results in a 1.58% increase in total emissions relative to the "UAM without ridesharing" scenario (Scenario 2), whereas for all other EV adoption rates studied, UAM with ridesharing provided the lowest emissions. Fortunately, these increases in emissions are relatively minuscule and should not pose limits on large-scale UAM operations. Figure 7 demonstrates that the effect of increasing EV usage on emissions reduction is far greater than that of introducing ridesharing-enabled UAM operations.

B. Average UAM Trip Emissions

A natural extension to the analysis presented in Fig. 7 is to determine how emissions associated with a UAM-preferring passenger would change had they performed their trip fully on the ground instead. In other words, we are interested in determining whether UAM-preferring passengers would emit more or fewer emissions between various modes of travel, and to what extent. This question is answered in Fig. 8, which is a microscopic evaluation of the results presented in Fig. 7 corresponding to the 7% EV utilization rate.

In Fig. 8, we present average emissions per trip on two different subsets of passenger-trips, both assuming a 7% EV utilization rate. In the case of UAM without ridesharing on the left-hand side of Fig. 8, we investigate emissions generated by the 2,907 passengers that have chosen the UAM mode, based on the effective cost metric, along with emissions generated had they instead chosen the car mode to complete their journey. Next, in the case of UAM with ridesharing on the right-hand side of Fig. 8, we consider the 154,093 UAM-preferring passengers that are flown on a total of 38,996 ridesharing-enabled UAM flights, in addition to their respective individual first- and last-mile car segments. We solve for their average emissions per trip, in addition to their average emissions had they chosen instead to take their own individual ground segments in the car mode.

In the UAM without ridesharing case, a passenger selecting the car mode in lieu of the UAM mode to complete their trip would generate 42.9% less emissions on average. In contrast, with UAM ridesharing, a passenger selecting the car mode in lieu of the UAM mode would generate 48.2% more emissions on average. This advantage of ridesharing-enabled UAM over the car alternative in terms of average emissions generated per passenger trip is caused in part by the fact that ridesharing-enabled UAM segments contain on average nearly four passengers per flight in our modeling, as opposed to the single-passenger car alternative. This also helps explain why enabling UAM ridesharing causes a drop in total network-wide emissions relative to other scenarios across most EV utilization rates, as shown in Fig. 7.

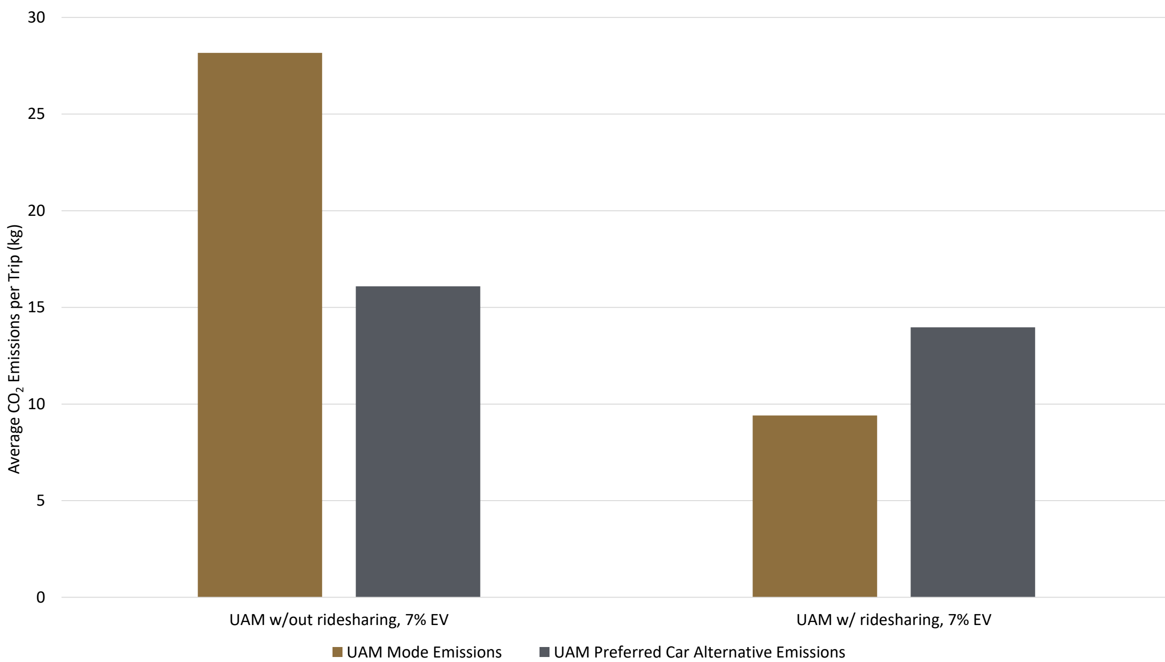

Fig. 8 Average emissions per passenger-trip for all UAM-preferred trips in the Chicago full aerodrome network, compared alongside the average emissions per passenger-trip for those same UAM-preferred trips, but calculated as individual car-based travel for two scenarios assuming a 7% EV utilization rate: a non-ridesharing UAM network and a ridesharing UAM network. Results indicate that without ridesharing, the car alternative has less emissions; however, with ridesharing applied, the UAM mode has lower emissions per trip than the car mode.

In comparing the left and right sets of bars in Fig. 8, enabling UAM ridesharing reduces the overall average emissions associated with the entire UAM mode of travel, which involves ground segments to and from aerodromes in addition to the UAM segment between aerodromes. This reduction is approximately 67%, or nearly three-fold. Emissions generated from the car alternative in going from UAM without ridesharing to UAM with ridesharing have also slightly decreased. This is likely due to the nature of the trip origins and destinations that occur under both scenarios, where UAM-preferred trips are on average shorter with ridesharing than without ridesharing.

C. Varying Grid Emission Index Values

Figure 9 demonstrates a more isolated sensitivity analysis, showing how the total daily transportation emissions in the Chicago metro area may change as the electricity grid emissions index varies, assuming a "UAM with ridesharing" scenario. In order to complete this sensitivity analysis, we picked an arbitrary grid emission index value reduction of 30%, a 55% reduction as projected by the EIA by 2050, and a 98% reduction to simulate a fully renewable grid powered by onshore wind. Although these results are not meant to represent yearly projections of how the electric grid index may change, they provide a general representation of the effects of continuously changing electric grid compositions. We have included a 7% and an 80% EV utilization rate to compare total emissions sensitivities between various EV utilization rates and a breakdown of the total emissions from the car mode as well as the UAM mode.

As the grid emissions index is reduced, there is a slight decrease in total emissions as well as in emissions generated by the UAM mode across all grid emissions index scenarios. This is to be expected, as emissions generated from UAM operations depend directly on the EI_{GRID}, as do the emissions generated from the EVs that are utilized in the network. This demonstrates that any reduction in EI_{GRID} will always have a positive impact on emissions (assuming all other factors remain constant), and as more grid-dependent vehicles are added to the network, the relationship between the EI_{GRID} value and the total emissions becomes even more apparent. However, we also observe that changes in the EV utilization rate produce a greater impact on total emissions reduction than equivalent changes in the EI_{GRID}. Jumping from a 7% to an 80% EV utilization rate causes total emissions to drop by at least 50% for all EI_{GRID} values, and this effect becomes more pronounced as the EI_{GRID} is reduced. Even at very low, idealized EI_{GRID} values, a large increase in

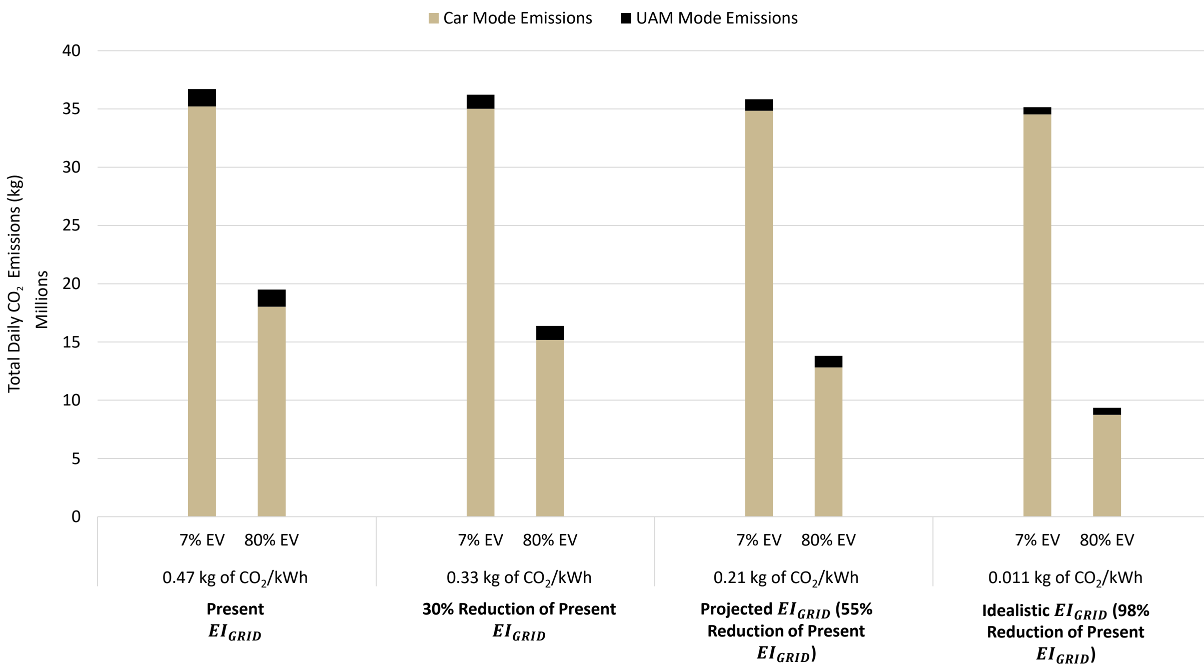

Fig. 9 Impact of EI_{GRID} on total emissions for passenger trips in the Chicago metro area (full 70-aerodrome network) with 7% and 80% EV utilization rates and UAM ridesharing applied. A clear, but small emissions reduction trend emerges with decreasing EI_{GRID}, while there is a larger reduction trend with increasing EV utilization rate.

the EV utilization rate beyond 7% is needed to begin to reap the emissions reduction benefits of such a clean electric grid. Increasing the EV utilization rate from 7% to 80% results in an almost 17 million kilogram difference under the present EI_{GRID} value of 0.47 kg/kWh, but a reduction of this EI_{GRID} value down to 0.011 kg/kWh results in only a 1.5 million kilogram reduction under the 7% EV utilization rate.

D. Obtaining Total Emissions across All Scenarios

Figure 10 represents a culmination of all the analyses and sensitivity sweeps performed in this study, and depicts total CO_2 emissions (the aggregate of all vehicle types and daily trips completed in the network) across seven different scenarios, taking into account various degrees of EV adoption and UAM and UAM ridesharing scenarios, each with variations in the emissions grid index. Broadly incorporating these scenarios into our emissions analyses will assist in accounting for possible current and hypothetical future states of the Chicago metro area travel network, including the leftmost scenario which closely reflects present-day conditions.

The three columns on the left represent changes in UAM and UAM ridesharing scenarios, while holding constant the EV utilization rate at 7%. Introducing single-passenger UAM operations results in negligible changes to total emissions relative to the no-UAM scenario. However, it is not until ridesharing is introduced in UAM services that emissions would begin to drop meaningfully across various grid emissions index values. The third through sixth columns demonstrate significant total emissions reductions with large increases in EV utilization. Finally, a no-UAM, full-EV utilization scenario, corresponding to the seventh column, was added to our analyses for the purposes of comparison with a ridesharing-enabled UAM, full-EV utilization scenario represented on the sixth column. Although we observe that involving UAM operations on top of a full-EV ground network will result in an increase in total emissions, these increases do not exceed 2% and are almost negligible, especially at lower grid emissions index values. Furthermore, a purpose of enabling ridesharing in UAM operations is to expand economic accessibility to more passengers. Although UAM ridesharing may effect substantial time and cost savings for many passengers, they would be realized at the small expense of emissions increases in order to support the improvement of transportation services in Chicago and bring about an "integrated sustainability" of UAM operations.

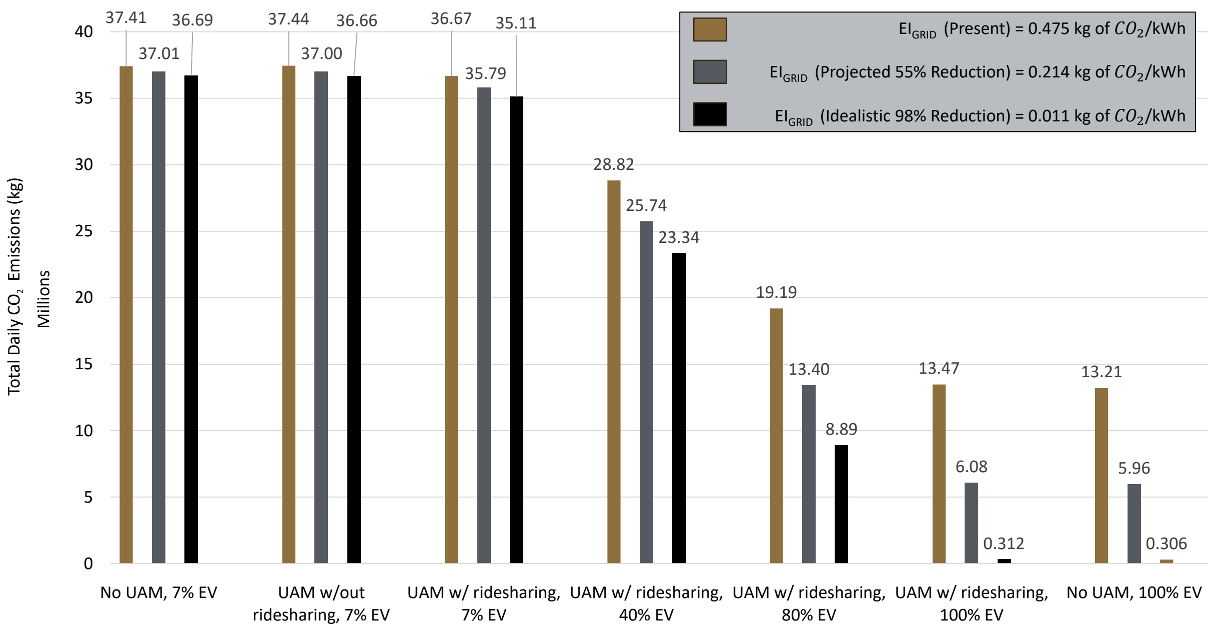

Fig. 10 Aggregated emissions for each scenario at three different EI_{GRID} values: Present, Projected, and Idealistic. The left-most scenarios in the figure depict a more current travel network that may be present in Chicago, whereas the right-most scenarios depict a more futuristic travel network, with the extreme increase in EV usage. The figure illustrates the large changes in total emissions as EV implementation increases, as well as confirming that applying ridesharing to the UAM network will continue to reduce emissions.

Finally, we note that the scenarios become progressively more reliant on the electric grid from the left to the right. This explains why the emissions drops in each scenario caused by a reduction in the grid emissions index become "steeper" with every successive scenario depicted in Fig. 10. The emissions totals presented in Fig. 10 are detailed further in Appendix A.

V. Conclusions and Future Work

This paper investigated various degrees of adoption of battery-powered electric vehicles, single-passenger UAM service, and ridesharing-enabled UAM service, under a varying electric grid, and their impact on carbon dioxide emissions across several distinct scenarios. This investigation was made for the Chicago metro area 70-aerodrome travel network as a case study on the resulting total network-wide emissions.

We developed a method for modeling emissions based on previous work [7] and modified the analysis process to be able to view results by each vehicle type available in a network or by the mode of travel for an origin-to-destination trip. We completed a sensitivity analysis by looking at the general bounds of variation on the grid emissions index in order to understand where operational limits that relate to emissions may lie. We were also able to complete multiple scenario comparisons that illustrated trends with increasing electric vehicles and applying ridesharing to a UAM network. Note that we do not consider emissions from battery manufacturing and vehicle production in our calculations at this time.

Although improved modeling is still needed, these preliminary results appear to indicate that CO_2 emissions may not be a major operational limit to UAM operations at scale. Implementing UAM, even with the expected changes in EV utilization and incorporating ridesharing into the UAM mode, could result in a net reduction of emissions in the Chicago metropolitan area, according to our analysis. Furthermore, ridesharing implementation intends to increase economic accessibility to the UAM network, augmenting travel options in a metro area. Our results showed that, on average, each UAM passenger trip in a non-ridesharing UAM network had more emissions than if the passenger took an automobile instead for their travels, but this was reversed once ridesharing is enabled in the UAM network. We found that enabling ridesharing in UAM is generally beneficial for emissions on a per passenger basis but results in a small increase in aggregate emissions compared to a no-UAM travel network.

Overall, the integration of electric automobiles (EVs) into the ground network will greatly improve the emissions picture in Chicago in any scenario studied, regardless of the electricity grid emissions index, EI_{GRID}, value or if ridesharing is applied on the network. When varying EI_{GRID}, there are only small reductions in emissions performance as compared to when EV utilization is increased. Improvement of the EI_{GRID} will become more significant once more of the network is reliant on the electricity grid for energy (i.e., when more EVs are involved and/or more UAM trips are included in the travel network). It should be noted that our variations of the electric grid emissions are based on the aggregate value for the entire grid.

Future work is planned to assess emissions in a similar fashion, incorporating UAM ridesharing, across other metro areas that have been analyzed previously without UAM ridesharing, including Cleveland, OH; Dallas, TX; Denver, CO; New York City, NY; Orlando, FL; and San Francisco, CA, in order to obtain a more comprehensive view of network-wide total emissions across various US metropolitan areas with their distinct characteristics and geography. Including these new metros will also involve assigning parameters, such as projected EV utilization rates and grid emissions index projections, specific to each metro. Future enhancements to the ridesharing model may also warrant a revisit of emissions modeling in conjunction with analyses on aerodrome throughput and weather operations limits that limit the scale of UAM operations.

VI. Acknowledgements

This work is funded by the National Aeronautics and Space Administration (NASA) via the Logistics Management Institute under the contract number DATSS 80HQTR18A0013- 80HQTR23F0116 (TO#70). The final two authors were supported by the AAM Mission Integration Office and the Intercenter Systems Analysis Team, which are both funded by the NASA Aeronautics Research Mission Directorate. The authors would like to thank NASA's Jim Murphy and Yuri O. Gawdiak for valuable feedback during the course of this project. The background map data in Fig. 2 is available under the Open Database License [20].

References

[1] Garrow, L. A., German, B., Schwab, N. T., Patterson, M. D., Mendonca, N., Gawdiak, Y. O., and Murphy, J. R., "A Proposed Taxonomy for Advanced Air Mobility," *AIAA AVIATION 2022 Forum*, 2022, p. 3321. doi:10.2514/6.2022-3321.

[2] Thipphavong, D. P., Apaza, R., Barmore, B., Battiste, V., Burian, B., Dao, Q., Feary, M., Go, S., Goodrich, K. H., Homola, J., et al., "Urban Air Mobility Airspace Integration Concepts and Considerations," *2018 Aviation Technology, Integration, and Operations Conference*, 2018, p. 3676. doi:10.2514/6.2018-3056.

[3] Archer, "Archer Announces Commitment to Launching its Urban Air Mobility Network in Miami by 2024 — news.archer.com," `https://news.archer.com/archer-announces-commitment-to-launching-its-urban-air-mobility-network-in-miami-by-2024`, 2021. Accessed: 2024-06-10.

[4] Joby Aviation, "Joby Flies Quiet Electric Air Taxi in New York City," `https://www.jobyaviation.com/news/joby-flies-quiet-electric-air-taxi-new-york-city/`, 2024. Accessed: 2024-06-10.

[5] Gipson, L., "Advanced Air Mobility National Campaign Partners," `https://www.nasa.gov/directorates/armd/advanced-air-mobility-national-campaign-partners/`, 2021. Accessed: 2023-12-20.

[6] DeLaurentis, D., "Understanding Transportation as a System-of-Systems Design Problem," *43rd AIAA Aerospace Sciences Meeting and Exhibit*, 2005, p. 123. doi:10.2514/6.2005-123.

[7] Mudumba, S. V., Chao, H., Maheshwari, A., DeLaurentis, D. A., and Crossley, W. A., "Modeling CO2 Emissions From Trips Using Urban Air Mobility and Emerging Automobile Technologies," *Transportation Research Record*, Vol. 2675, No. 9, 2021, pp. 1224–1237. doi:10.1177/03611981211006439.

[8] Kasliwal, A., Furbush, N. J., Gawron, J. H., McBride, J. R., Wallington, T. J., Kleine, R. D. D., Kim, H. C., and Keoleian, G. A., "Role of Flying Cars in Sustainable Mobility," *Nature Communications*, Vol. 10, No. 1555, 2019. doi:10.1038/s41467-019-09426-0.

[9] Holdway, A. R., Williams, A. R., Inderwildi, O. R., and King, D. A., "Indirect Emissions from Electric Vehicles: Emissions from Electricity Generation," *Energy & Environmental Science*, Vol. 3, No. 12, 2010, pp. 1825–1832. doi:10.1039/C0EE00031K.

[10] Uber, "Uber Elevate: Fast-Forwarding to a Future of On-Demand Urban Air Transportation," https://d1nyezh1ys8wfo.cloudfront.net/static/PDFs/Elevate%2BWhitepaper.pdf, 2016. Accessed: 2024-05-31.

[11] Chen, Z., Carrel, A. L., Gore, C., and Shi, W., "Environmental and Economic Impact of Electric Vehicle Adoption in the US," *Environmental Research Letters*, Vol. 16, No. 4, 2021, p. 045011. doi:10.1088/1748-9326/abe2d0.

[12] Thipphavong, D. P., "Analysis of Electrical Grid Capacity by Interconnection for Urban Air Mobility," *AIAA AVIATION 2022 Forum*, 2022, p. 3316. doi:10.2514/6.2022-3316.

[13] Maheshwari, A., Mudumba, S., Sells, B. E., DeLaurentis, D. A., and Crossley, W. A., "Identifying and Analyzing Operations Limits for Passenger-Carrying Urban Air Mobility Missions," *AIAA AVIATION 2020 FORUM*, 2020, p. 2913. doi:10.2514/6.2020-2913.

[14] Maheshwari, A., Sells, B. E., Harrington, S., DeLaurentis, D., and Crossley, W., "Evaluating Impact of Operational Limits by Estimating Potential UAM Trips in an Urban Area," *AIAA AVIATION 2021 FORUM*, 2021, p. 3174. doi:10.2514/6.2021-3174.

[15] Sells, B. E., Iyengar, K., Kim, B., Gunady, N., Wright, E., Patel, S. R., DeLaurentis, D. A., and Crossley, W. A., "A Comparative Study of Aerodrome-Related Operational Limits for Passenger-Carrying Missions across Metropolitans," *AIAA AVIATION 2023 Forum*, 2023, p. 3410. doi:10.2514/6.2023-3410.

[16] Mane, M., and Crossley, W. A., "Importance of Aircraft Type and Operational Factors for Air Taxi Cost Feasibility," *Journal of Aircraft*, Vol. 46, No. 4, 2009, pp. 1222–1230. doi:10.2514/1.40146.

[17] Chao, H., Maheshwari, A., DeLaurentis, D., and Crossley, W., "Weather Impact Assessment for Urban Aerial Trips in Metropolitan Areas," *AIAA AVIATION 2021 FORUM*, 2021, p. 3176. doi:10.2514/6.2021-3176.

[18] Biswas, S. D., Edsel, A., Gadre, R., Kilbourne, M., Vashi, S., Mall, K., DeLaurentis, D. A., Crossley, W., and Patterson, M. D., "Passenger Aggregation Network with Very Efficient Listing (PANVEL) Ride-Sharing Model for Advanced Air Mobility," *AIAA AVIATION 2024 Forum*, 2024. Manuscript accepted.

[19] Federal Aviation Administration, "Airport Data & Information Portal," https://adip.faa.gov/agis/public/#/public, 2023. Accessed: 2023-12-10.

[20] OpenStreetMap Contributors, "OpenStreetMap," https://www.openstreetmap.org/copyright, 2024. Accessed: 2024-04-12.

[21] The United States Census Bureau, "Longitudinal Employer-Household Dynamics," https://lehd.ces.census.gov/data/, 2023. Accessed: 2023-12-11.

[22] The United States Census Bureau, "American Community Survey," https://www.census.gov/programs-surveys/acs, 2023. Accessed: 2023-12-11.

[23] Uber, "Uber Elevate Summit 2018: Live Stream Day 1 (Part 1)," https://www.youtube.com/live/hnceMcSnjQ0?t=2930s, 2018. Accessed: 2024-05-31.

[24] Roy, S., Maheshwari, A., Crossley, W. A., and DeLaurentis, D. A., "A Study on the Impact of Aircraft Technology on the Future of Regional Transportation Using Small Aircraft," *2018 Aviation Technology, Integration, and Operations Conference*, 2018, p. 3056. doi:10.2514/6.2018-3056.

[25] Roy, S., Maheshwari, A., Crossley, W. A., and DeLaurentis, D. A., "A Study to Investigate Total Mobility Using Both CTOL and VTOL-Capable Aircraft," *AIAA AVIATION 2019 Forum*, 2019, p. 3518. doi:10.2514/6.2019-3518.

[26] Roy, S., Maheshwari, A., Crossley, W. A., and DeLaurentis, D. A., "Future Regional Air Mobility Analysis Using Conventional, Electric, and Autonomous Vehicles," *Journal of Air Transportation*, Vol. 29, No. 3, 2021, pp. 113–126. doi:10.2514/1.d0235.

[27] Sells, B. E., Maheshwari, A., Chao, H., Wright, E., Crossley, W., and Sun, D., "Evaluating the Impact of Urban Air Mobility Aerodrome Siting on Mode Choice," *AIAA AVIATION 2021 FORUM*, 2021, p. 2371. doi:10.2514/6.2021-2371.

[28] Environmental Protection Agency, "Power Profiler | US EPA," https://www.epa.gov/egrid/power-profiler, 2023. Accessed: 2023-12-11.

[29] Austin, D., "Modeling the Demand for Electric Vehicles and the Supply of Charging Stations in the United States," *Working Paper Series, Congressional Budget Office, Washington, D.C.*, 2023, p. 47.

[30] U.S. Energy Information Administration (EIA), "Annual Energy Outlook 2023," https://www.eia.gov/outlooks/aeo/, 2023. Accessed: 2024-03-30.

[31] Intergovernmental Panel on Climate Change, "Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," https://www.ipcc.ch/report/ar5/wg3/, 2014. Accessed: 2024-06-21.

[32] Barth, M., and Boriboonsomsin, K., "Real-World Carbon Dioxide Impacts of Traffic Congestion," *Transportation Research Record*, Vol. 2058, No. 1, 2008, pp. 163–171. doi:10.3141/2058-20.

[33] International Energy Agency, "Comparative Life-Cycle Greenhouse Gas Emissions of a Mid-Size BEV and ICE Vehicle," https://www.iea.org/data-and-statistics/charts/comparative-life-cycle-greenhouse-gas-emissions-of-a-mid-size-bev-and-ice-vehicle, 2021. Accessed: 2024-06-20.

A. Appendix

Table 2 Characteristics of the UAM aircraft utilized in the travel network, including necessary energy outputs

Characteristic	Value
Climb Energy (kWh)	5.80
Cruise Energy (kWh)	124.61 × Cruise Duration (hours)
Hover Energy (kWh)	6.42
Descent Energy (kWh)	2.30
Cruise Speed (mph)	150
Passenger Capacity	4
Nonstop Range (nmi)	50
Direct Operating Cost ($/hour)	605 [13, 23, 25]

Table 3 Daily CO_2 emissions by vehicle type across seven scenarios and three grid emissions index values

Scenarios	EI_{GRID}	ICE Car Daily CO_2 Emissions (kg)	EV Car Daily CO_2 Emissions (kg)	UAM Aircraft Daily CO_2 Emissions (kg)
Scenario 1 No UAM 7% EV	Present	36,676,520	730,614	0
	Projected	36,676,520	329,871	0
	Idealistic	36,676,520	16,922	0
Scenario 2 UAM w/out ridesharing 7% EV	Present	36,640,921	730,370	70,935
	Projected	36,640,921	329,760	32,027
	Idealistic	36,640,921	16,916	1,643
Scenario 3 UAM w/ ridesharing 7% EV	Present	35,072,160	710,697	887,724
	Projected	35,072,160	320,878	400,805
	Idealistic	35,072,160	16,461	20,561
Scenario 4 UAM w/ ridesharing 40% EV	Present	23,206,960	4,728,398	887,724
	Projected	23,206,960	2,134,860	400,805
	Idealistic	23,206,960	109,516	20,561
Scenario 5 UAM w/ ridesharing 80% EV	Present	8,641,596	9,660,408	887,724
	Projected	8,641,596	4,361,651	400,805
	Idealistic	8,641,596	223,748	20,561
Scenario 6 UAM w/ ridesharing 100% EV	Present	0	12,586,558	887,724
	Projected	0	5,682,800	400,805
	Idealistic	0	291,522	20,561
Scenario 7 No UAM 100% EV	Present	0	13,206,667	0
	Projected	0	5,962,778	0
	Idealistic	0	305,884	0

Table 4 Daily CO_2 emissions totals across seven scenarios and three grid emissions index values

Scenarios	EI_{GRID}	Total Daily CO_2 Emissions (kg)	% change from Scenario 1
Scenario 1 No UAM 7% EV	Present	37,407,134	-
	Projected	37,006,390	-
	Idealistic	36,693,442	-
Scenario 2 UAM w/out ridesharing 7% EV	Present	37,442,227	0.1%
	Projected	37,002,709	-0.01%
	Idealistic	36,659,481	-0.1%
Scenario 3 UAM w/ ridesharing 7% EV	Present	36,670,580	-2%
	Projected	35,793,843	-3.3%
	Idealistic	35,109,181	-4.3%
Scenario 4 UAM w/ ridesharing 40% EV	Present	28,823,082	-22.9%
	Projected	25,742,626	-30.4%
	Idealistic	23,337,037	-36.4%
Scenario 5 UAM w/ ridesharing 80% EV	Present	19,189,728	-48.7%
	Projected	13,404,052	-63.8%
	Idealistic	8,885,905	-75.8%
Scenario 6 UAM w/ ridesharing 100% EV	Present	13,474,282	-64.0%
	Projected	6,083,605	-83.6%
	Idealistic	312,082	-99.1%
Scenario 7 No UAM 100% EV	Present	13,206,667	-64.7%
	Projected	5,962,778	-83.9%
	Idealistic	305,884	-99.2%