Flight Scheduling and Fleet Sizing for an Airport Shuttle Air Taxi Service

Article *in* Journal of Air Transportation · February 2022

DOI: 10.2514/1.D0265

5 authors, including:

Satadru Roy
ALCIFO Inc.

Mark T Kotwicz Herniczek
Georgia Institute of Technology

Flight Scheduling and Fleet Sizing for an Airport Shuttle Air Taxi Service

Satadru Roy*, Mark T. Kotwicz Herniczek†, Caroline Leonard‡, Brian J. German§, and Laurie A. Garrow¶
Georgia Institute of Technology, Atlanta, GA, 30332, U.S.A

A multi-commodity network flow framework for optimal flight scheduling for an envisioned airport shuttle air taxi service is presented. The framework includes a trip generation model that simulates requests from individuals who travel to and from the airport and are willing to pay for the travel time savings associated with an airport shuttle air taxi service. The framework can be used to determine the fleet size required to satisfy a given user demand and to assess how an operator's profitability can be influenced by multiple factors including the population density and income distribution in a metropolitan area, fleet size, ticket price, and air taxi operating costs. The results for an example business airport shuttle service to and from Atlanta Hartsfield Jackson International Airport suggest that a viable business case is possible using electric-Vertical Take-Off and Landing aircraft. For example, the results for this Atlanta case study indicate that it is possible to have profitable business use-case with positive cash flow with a 4-seat aircraft with a 60-mile design range and a 150 mph cruise speed using a fleet size of five aircraft at a price point of $5 per passenger-mile during near-term small-scale operations.

I. Nomenclature

A	=	Set of all ports in the network
$Cost_m$	=	Trip cost for mode m
c_e	=	Operating cost on arc e
ds_e	=	Demand served on arc e
E_j	=	Set of all arcs in the network of aircraft j
f_e	=	Flight time on arc e
J	=	Set of all aircraft in the network

*Research Faculty, Daniel Guggenheim School of Aerospace Engineering; currently Chief Executive Officer, ALCIFO Inc., and AIAA Senior Member
†Ph.D. Candidate, Daniel Guggenheim School of Aerospace Engineering, and AIAA Student Member
‡Graduate Research Assistant, School of Civil and Environmental Engineering
§Associate Professor, Daniel Guggenheim School of Aerospace Engineering, and AIAA Associate Fellow
¶Professor, School of Civil and Environmental Engineering, and AIAA Member

$P_{m,i}$ = Probability of an individual i taking mode m

$q_e^{a,b,t}$ = Capacity consumed on arc e for flight from a to b, departing a at time t

r_e = Revenue generated on arc e

s_e^r = Binary variable that takes the value of 1 if the trip request r is satisfied on arc e, 0 otherwise

$time_m$ = Trip time for mode m

$U_{m,i}$ = Theoretical utility for individual i taking mode m

$V_{m,i}$ = Observed utility for individual i taking mode m

V_j = Set of all nodes in the network of aircraft j

VoT_i = Value of travel time for the individual i

$VoTS_i$ = Value of travel time saved for the individual i

$w_e^{a,b,t}$ = Passenger weight on arc e for flight from a to b, departing a at time t

x_e = Binary design variable that takes the value of 1 if arc e in the aircraft network is selected, 0 otherwise

II. Introduction

The development of Urban Air Mobility (UAM) faces several important challenges including estimating the required fleet size to match supply to travel demand and assessing the impact of top-level aircraft requirements on the profitability of the operator. In other words, how many aircraft would be required for an initial UAM service to meet a certain level of demand with minimal deadhead flights, and what are the aircraft-level requirements that would lead to a viable business case? Answering these questions is a complex undertaking because of the strong couplings of aircraft design with factors including operations, market demand, infrastructure, costs, and ticket pricing.

A number of studies have examined some of these factors in the context of UAM [1–12]. Among the limited literature that seeks to assess aircraft performance requirements and operations in the context of urban air taxis, Ha *et al.* [13] considered operational variables to determine the feasibility of an eVTOL concept's design parameters in varying cruise and hover mission profiles. Shihab *et al.* [14] developed a decision and dispatch model for on-demand and scheduled flights based on simulated market demand. Hamilton and German [15] proposed a method to optimize cruise air speeds for scheduled electric aircraft operations. Narkus-Kramer *et al.* [16] examined trade-offs associated with battery-powered, remotely piloted semi-autonomous personal aircraft and assessed the feasibility of on-demand aviation in terms of market demand, climate change impact, net present value, and quality of service using a series of linked parametric models. The study by Narkus-Kramer *et al.* [16] found that profitability is closely tied to high network utilization and high daily aircraft utilization. Despite these initial efforts, there is still a need for comprehensive methods to model the relevant factors related to aircraft requirements and operations and the associated couplings between these factors [17, 18].

In this paper, we present a framework to model these factors and their couplings to estimate the required fleet size and profitability of an airport shuttle air taxi service. We describe a methodology that includes: (1) consideration of top-level aircraft characteristics, (2) a model that mimics the daily operations of the air taxi service, (3) a market demand model that considers census-tract socioeconomic information, (4) consideration of existing aviation infrastructure that can be used for potential landing sites, and (5) an econometric model for ticket pricing. The methodology is then leveraged to understand how aircraft-level characteristics affect the fleet-level performance of the operator.

Our first key contribution is to implement an algorithm for optimally scheduling flights for an eVTOL airport shuttle service for day-to-day operations of an on-demand UAM operator. The optimization of flight schedules for on-demand operations is not new. Martin *et al.* [19] proposed a system, called FlightOps, that handles all aspect of fractional fleet management including optimized flight scheduling for a fractional aircraft operator. Munari and Alvarez [20] recently proposed an approach that assigns aircraft to on-demand requests while accounting for maintenance events, allowing flight upgrades in order to reduce operational and re-positioning costs. In this effort, our contribution is to formulate the flight schedule optimization posed as a multi-commodity flow problem based on modifications to the original formulation of Espinoza *et al.* [21] which DayJet used for scheduling air taxi operations with the Eclipse 500 very light jet. The unique feature of this multicommodity network flow approach is that it is based on a time-activity network (as opposed to the traditional time-space network) in which it is easier to handle the constraints that limits the number of intermediate stops to at most one. With the time-activity based multi-commodity network, it is possible to obtain high-quality solutions to realistic, large-scale instances of the dial-a-flight problem [21, 22] within a reasonable computational time frame. Like Espinoza, we presume that flights are scheduled one day in advance, with customers specifying their earliest allowable departure times and latest allowable arrival times, and we require each aircraft to begin and end its day at a particular airport or heliport for compatibility with crew schedules and stationing. The scheduling approach also allows up to a maximum of one stop per passenger to pick up or drop other passengers along the way to facilitate ride-sharing.

However, unlike the original optimization problem formulation in [21] that minimizes the fleet-level operating cost, we implemented a bi-level problem formulation that first maximizes the demand to estimate how many aircraft the operator would need to satisfy the given number of generated trip requests and then optimizes the schedule such that the profit is maximized. The reason for the bi-level formulation — another key contribution in this paper — is that we do not have information on the total number of aircraft needed to satisfy the given trip requests and the demand maximization formulation allows us to obtain, in an iterative approach, the minimum number of aircraft needed to satisfy a certain threshold of demand.

Another important contribution of our work is the development of a trip generation model for the airport shuttle trip and its integration with the dispatch algorithm. The trip generation model is based on information about home-work origin locations for passengers who travel to the airport and a car versus eVTOL mode choice model [3] based on trip time, trip cost, traveler's value of time, and time-of-day distributions of flight arrivals and departures at the airport.

The paper is organized as follows. First we describe the components of the optimization framework, namely the trip generation model, a simplified aircraft model, and the integer multicommodity network flow model. Next, we present an optimized schedule for a simple set of trip requests to illustrate the functionality of the dispatch algorithm. Subsequently, we discuss the results demonstrating the application of the dispatch algorithm to an airport shuttle air taxi service in Atlanta and compare the fleet-level performance between a representative helicopter and an eVTOL aircraft model. Finally, we present a sensitivity analysis showing the trade-off among aircraft-level characteristics and the fleet-level performance that demonstrates a strong coupling among these disciplines necessitating the need for a holistic approach.

III. Framework

Our framework relies on a number of components including a demand model, an aircraft performance model, and a flight dispatch model. Each of these components is described below.

A. Demand Model

The demand model is responsible for providing a set of realistic trip requests to the dispatch model. The following information is provided for each trip request:

- Trip origin
- Trip destination
- Earliest departure time at origin port
- Latest arrival time at destination port

Trip requests are generated from an approximation of a typical day of operations of the airport shuttle service by leveraging the Atlanta Regional Commission's (ARC) airport survey data [23] and implementing a utility-based passenger choice model that estimates how many customers would be willing to take the air taxi service relative to ground transportation. In this work, we assumed that all trip requests are known prior to operation such that the dispatcher can consider all trip requests simultaneously. Trip destinations are either ATL airport or one of the trip origin locations (for example, travelers returning home from ATL). Passenger weight (including luggage) is assumed to be 220 lbs, and passengers are assumed to book the flight independently, i.e. each trip request corresponds to no more than one passenger.

1. Passenger Choice Model

We utilized a utility-based passenger choice model, based on our prior study [3], to simulate the expected behavior of individuals with regards to their choice of transportation mode to aid in the selection of trip origins and port locations. Similar to our prior study [3], an individual is presumed to have only has two available modes of transportation to the major airport: driving by car or taking the eVTOL air taxi service. For the air taxi mode, the individual first drives to the nearest port (our general term for a regional airport or a helipad) and then takes the eVTOL aircraft to travel to the major airport. The model determines the probability that an individual i will take the eVTOL air taxi mode as given by:

$$P_{eVTOL,i} = \frac{1}{1 + \exp(V_{auto,i} - V_{eVTOL,i})} \tag{1}$$

where,

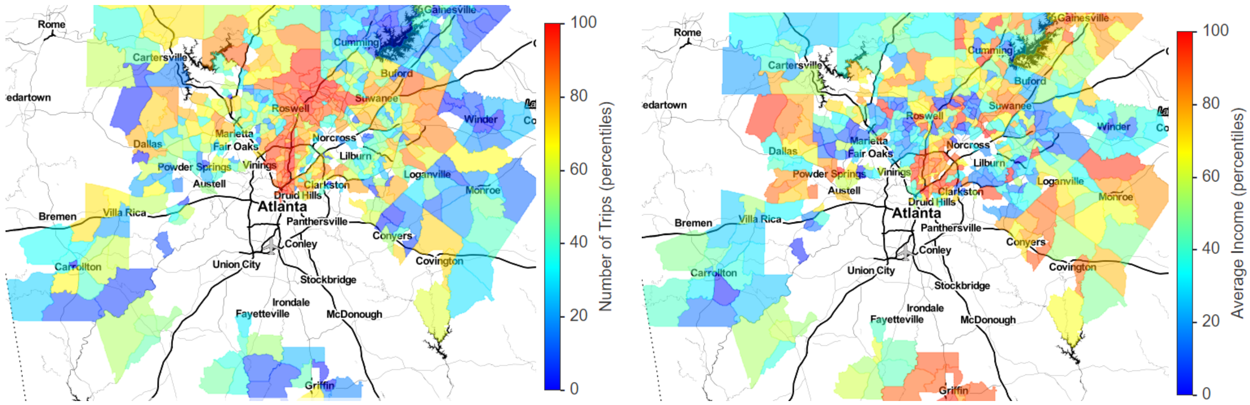
$$V_{auto,i} - V_{eVTOL,i} = (Cost_{eVTOL} - Cost_{auto}) + VoTS_i * (Time_{eVTOL} - Time_{auto}) \tag{2}$$

In the above equation, $VoTS_i$ is the value of time savings for the individual i. For a business trip, the value of time savings is typically assumed to equal 80-120% of the hourly household income of the individual [24], whereas for a personal trip the factor ranges between 60% and 90%. For the results presented in this paper, we used a factor of 1 to relate an individual's value of time savings to their hourly income.

To estimate the annual income of airport commuters, data sets from both the Atlanta Regional Commission (ARC) survey and American Community Survey (ACS) are leveraged. The former provides originating tracts of commuters traveling to and from ATL airport (illustrated in Fig. 1a) discretized over several coarse income brackets. The latter provides additional tract-level income data, which are used to refine estimates of the annual income of airport commuters. This is done by fitting a Weibull distribution to each tract using ACS data for incomes up to \$200,000. Incomes above \$200,000, which typically behave according to the Pareto principle [25, 26], are fitted using a power law using the number of individuals earning above \$200,000 within a tract and the mean income of the tract [3].

Random samples are then taken from slices of each distribution in accordance with the ARC survey data. For example, the ARC data may estimate that 40 individuals with incomes between \$60,000 and \$120,000 travel from a specific tract to the airport on a daily basis. Discrete incomes are obtained for these individuals by sampling the portion of the Weibull distribution for that tract between \$60,000 and \$120,000. Airport commuters from the ARC survey with no specified income bracket are sampled from both the full Weibull distribution and the high-income power-law distribution. An important assumption made here is that airport users have the same income distribution as the general population of a tract, which likely skews the presented results to more conservative values since airport users are expected to have, on average, higher incomes than the general population.

The geographical distribution of the estimated income of airport commuters (averaged at a tract level) appears in Fig. 1b. A concentration of trip requests and high income individuals can be observed in Figs. 1a and 1b near the central north portion of the Atlanta region, corresponding to the affluent suburban cities of Sandy Springs, Roswell, and Milton, and the neighborhood of Buckhead. Blank tracts in Figs. 2 to 3 are due to lack of data for those regions in the ARC survey. Following the process described above, we have modeled the origins and annual income (and hence, the value of time) of individuals traveling to ATL.



(a) Location of airport commuters according to ARC survey

(b) Estimated average income of airport commuters

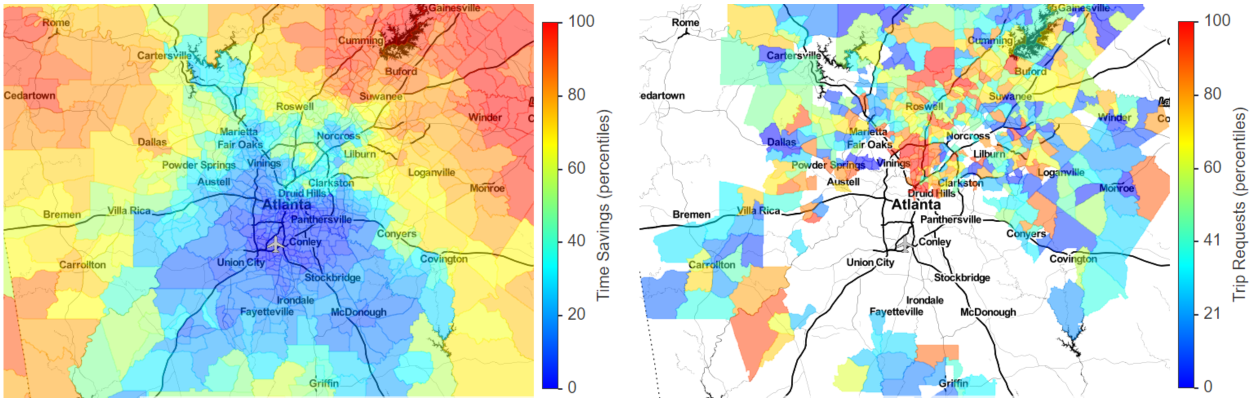
Fig. 1 Geographical representation of ARC and ACS data for the Atlanta region

2. Trip Origins and Port Selection

The utility-based decision model described in the previous section is leveraged to identify which individuals traveling to ATL can be expected to utilize the UAM airport shuttle service. The utility-based model estimates an individual's behavior based on the relative utility of using the air taxi airport shuttle service compared to ground transportation i.e., driving by car. Essentially, the utility of each mode is computed by combining the cost of operation information with value of time estimates and trip duration data.

Operating cost data of the air vehicles are taken from the 2019 Uber Elevate Summit [27] and the travel duration of the ground segments of the trip are estimated using the Bing Maps API [28]. The trip duration for the first and last mile ground segment of the airport shuttle air taxi service, depending on the time and weather conditions of the day, includes drive-time estimates from the origin/destination to the nearest port. As such, the locations of the ports directly impact the duration of the driving leg of the shuttle service, thereby affecting the utility of the airport shuttle service as a whole. Only existing ports, specifically public and private regional airports and helipads, which we collectively refer to as ports, are considered for the airport shuttle air taxi operations. Federal Aviation Administration (FAA) Airport Data [29] was used to identify airport and heliport locations.

The time savings expected for individuals using the airport shuttle service (assuming all 117 non-medical helipads and regional airports in the Atlanta metropolitan region are available as ports) and the resulting distribution of trip requests (again assuming all ports are available) are presented in Fig. 2. As illustrated in Fig. 2a, time savings increase for trips originating further away from ATL airport and away from major highways. As could be expected, the resulting distribution of trip requests, shown in Fig. 2b, is skewed towards tracts with a large number of people going to the airport, high average incomes, and that have the potential for significant travel time savings.



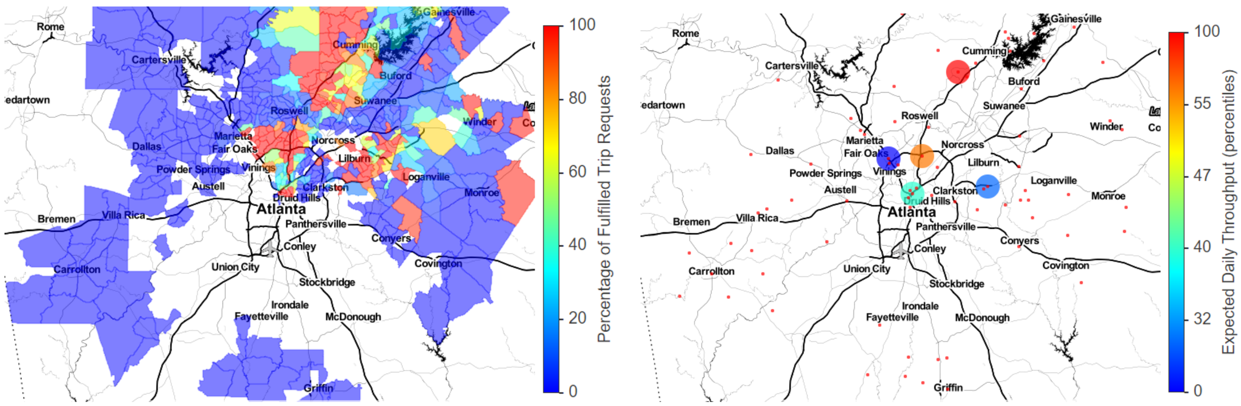
(a) Time savings of individuals using the airport shuttle service

(b) Distribution of trip requests prior to port downselection

Fig. 2 Time savings and distribution of potential origin and destination of trip requests for the Atlanta region

Appropriate selection of these port locations is necessary to maximize the market size for the UAM shuttle service assuming that only a subset of all existing infrastructure (non-medical helipads and regional airports) can be used for UAM operations. A simple combinatorial approach is used in the present effort due to the relatively small number of existing possible port locations within Atlanta. To find the combination of ports that maximizes the total number of customers (defined as individuals for whom the airport shuttle service provides a higher utility than ground transportation) in the Atlanta region, the utility of both transportation modes is computed for all possible combinations of ports and for all potential customers. More efficient approaches, however, will be necessary when evaluating larger and more populous regions such as New York City to avoid the combinatorics from becoming computationally intractable. Customers who would travel via UAM with the optimal set of port locations make up the market size of the airport shuttle service and are used to generate trip requests.

The percentage of the trip requests that is fulfilled by an optimized set of five ports and their locations are presented in Figs. 3a and 3b. As shown, a significant portion (61%) of the total trip requests from Fig. 2b can be captured from the Atlanta region using only 5 out of the 117 existing helipads and regional airports in region. The distribution of unused potential port locations are denoted by red dots in Fig. 3b. The current effort assumes that direct, straight-line (as the crow flies) flight paths are possible.



(a) Percentage of trip requests fulfilled by top 5 ports

(b) Optimized locations of top 5 ports

Fig. 3 Result of port selection process

3. Earliest Departure and Latest Arrival Times

All passengers in the demand model are presumed to be airline customers that are either arriving at or departing from ATL airport. To determine the temporal distribution of trips to and from the airport, a set of continuous probability density functions (PDFs) representing the number of passengers arriving and departing from the airport throughout the day are developed. These distributions combine information from the Bureau of Transportation Statistics data, which provides departure and arrival times by aircraft tail number (N-Number) [30], with passenger capacity data from the FAA aircraft database [31]. The generated arrival and departure PDFs are then randomly sampled to assign an arrival or departure time to each trip request.

Departure and arrival times are adjusted to account for the travel time of the airport shuttle service and to consider delays associated with entering and exiting the airport. For passengers departing from ATL, arrival times are adjusted based on [32], which provides departure-dependent distributions of arrival times to the airport. For passengers arriving in ATL, departure times are adjusted based on the total time required to exit an airport and assumed to be 45 minutes using data from [33] that includes the time it takes to walk to the port for the air taxi service. These arrival and departure times are average estimates over both domestic and international flights to and from the ATL airport.

B. Aircraft Model

The aircraft model, based on prior work [3], provides an estimate of the flight time and cost information for a given mission profile. Table 1 provides the characteristics of a representative eVTOL aircraft along with the characteristics of a representative helicopter, the Bell 407 GXi, used for comparison purposes later in this paper. The parameters in Table 1 are used to define a baseline aircraft and to support sensitivity studies showing how varying these aircraft parameters impact the fleet-level profit for the business airport shuttle air taxi mission to the ATL airport. Note that the seat count, presented in Table 1, excludes the extra seat needed to have a pilot onboard and assumes all flights are human-piloted.

Table 1 Baseline aircraft performance and cost data

Parameters	eVTOL	Helicopter
Cruise speed [mph]	150	153
Maximum range [mi]	60	388
Number of seats	4	6
Operating cost [$/hr]	662	1253

C. Integer Multicommodity Network Flow Model Based on a Time-Activity Network

The dispatch algorithm presented here is based on the prior work of Espinoza *et al.* [21] that uses an integer multicommodity network flow model with side constraints on a time-activity network. Each aircraft in the network is treated as a commodity and the approach populates a set of nodes and connecting arcs for every instance of time during the 24 hour day. The binary linear programming problem formulation finds the path for each aircraft that maximizes (or minimizes) the fleet-level goal of the operator. Each node represents the current state of the aircraft and the arcs connecting these nodes represent the movement of the aircraft in the network. The nodes represent the three key decisions for each aircraft in the model as it travels between the ports: A "standby" decision allows the aircraft to stay idle at an airport, the "departure" decision allows the aircraft to travel from one port to another, and the "loading" decision allows the aircraft to satisfy a trip request after the aircraft has made the departure decision to go to a different port. Once the feasible set of nodes and arcs are populated, the scheduler identifies the optimal set of nodes and arcs via a network flow formulation. A formal description of the nodes and arcs in the network, as presented in [21], appears below.

1. Defining the Nodes

1) **Standby Nodes** $S_j(a,t)$: Aircraft j is in the standby state, without any passengers on board, and is ready to takeoff from airport a at time instance t.
2) **Gate Nodes** $G_j(a,t,b)$: Aircraft j will takeoff from airport a at time t and fly to airport b.
3) **Direct Loading Nodes** $DL_j(a,t,b,r)$: Aircraft j satisfies request r with a direct flight from airport a to airport b, departing airport a at time instance t.
4) **Indirect Loading Nodes** $IL_j(a,t_1,b,t_2,c,r)$: Aircraft j indirectly satisfies request r by first flying from airport a at time instance t_1 to the intermediate airport b, and then leaving airport b at time instance t_2 to arrive at the airport c.
5) **Terminal Nodes** T_j^b, T_j^e: The model assumes each aircraft has a home base h from where it starts and ends its operation on a given day. The terminal nodes enforce this requirement and are defined as $T_j^b = S_j(h,t_s)$ and $T_j^e = S_j(h,t_e)$, where t_s and t_e are the time periods representing the beginning and end of a day's operations for the aircraft j.

2. Defining the Arcs

1) **Idle Arc**: Assign an arc from $S_j(a, t_1)$ to $S_j(a, t_2)$ for every airport a and every pair of time instants t_1, t_2.
2) **Departure Arc**: Assign an arc from $S_j(a, t)$ to $G_j(a, t, b)$ for every pair of airports a, b in the network and every time instant t.
3) **Loading Arc**: Introduce an arc from $G_j(a, t, b)$ to $DL_j(a, t, b, r)$ for every pair of airports a, b at every time instant t, for service request r that can be satisfied by a direct flight. Similarly, introduce an arc from $G_j(a, t, b)$ to $IL_j(a, t_1, c, t_2, b, r)$ for any request that can be satisfied by an indirect flight.
4) **Aggregation Arc**: Assign an arc connecting the two direct loading nodes for each pair of requests, r_1, r_2, with the same origin-destination pair and compatible departure times. Similarly, assign arcs between direct loading nodes and indirect loading nodes, and between two indirect loading nodes that have similar attributes. This aggregation arc identifies requests that can be combined in a single trip.
5) **Relocation Arc**: Generate an arc between $G_j(a, t_1, b)$ and $S_j(b, t_2)$ for each pair of airports a, b at every pair of time instants t_1, t_2, such that $t_2 = t_1 + t_{flight}(a, b) + t_{turnaround}$.
6) **Direct Flight Arc**: Assign an arc from $DL_j(a, t_1, b, r)$ to $S_j(b, t_2)$, where $t_2 = t_1 + t_{flight}(a, b) + t_{turnaround}$ for each pair of airports a, b, at each time instant t_1, and each trip request r.
7) **Indirect Flight Arc**: Similarly to the direct flight arc, assign an arc from $IL_j(a, t_1, b, t_2, c, r)$ to $G_j(b, t_2, c)$ for each pair of airports a, b at each time instant t_1, and each trip request r. Note that the indirect flight arc is connected to a gate node (rather than to a standby node, as in the direct flight arc case) as there are passengers on-board to be carried to a different destination airport.

Given a set of nodes V_j and arcs E_j for each aircraft j, the trip requests can be satisfied in many different ways by altering connections between nodes. Finding the optimal set of arcs to connect each node is a binary integer programming problem with linear objective and constraints. The binary design variable, x_e, represents the set of all the arcs that connect the nodes. It takes a value of 1 if an arc is present between the two nodes, otherwise it takes a value of 0. Mathematically, the problem formulation can be stated as,

$$\max \sum_{j}^{J} \sum_{e}^{E} ds_e x_e \quad \text{or} \quad \max \sum_{j}^{J} \sum_{e}^{E} (r_e - c_e) x_e \tag{3}$$

$$\sum_{e \in E_j : \text{tail}(e) = T_j^b} x_e = 1 \quad \forall j \in J \tag{4}$$

$$\sum_{e \in E_j : \text{head}(e) = T_j^e} x_e = 1 \quad \forall j \in J \tag{5}$$

$$\sum_{e \in E_j : \text{head}(e) = v} x_e = \sum_{e \in E_j : \text{tail}(e) = v} x_e \quad \forall v \in V_j \setminus [T_j^b, T_j^e] \quad \forall j \in J \tag{6}$$

$$\sum_{e \in E_j} q_e^{a,b,t} x_e <= \text{CAPACITY}(j) \quad \forall a, b \in A, \forall t \in T, \forall j \in J \tag{7}$$

$$\sum_{e \in E_j} w_e^{a,b,t} x_e <= \text{MAXWEIGHT}(j) \quad \forall a, b \in A, \forall t \in T, \forall j \in J \tag{8}$$

$$\sum_{e \in E_j} f_e x_e <= \text{MAXFLIGHTTIME}(j) \quad \forall j \in J \tag{9}$$

$$\sum_{j \in J} \sum_{e \in E_j} s_e^r x_e <= 1 \quad \forall r \in R \tag{10}$$

where, Eq. (3) is the objective function that seeks to maximize the total demand served or the fleet-level profit depending on the problem formulation as discussed below.

Table 2 shows a set of three hypothetical trip requests that need to be satisfied by the operator using a single aircraft. The first request involves a trip from port 2 to port 3. The individual is available for pick up at port 2, no earlier than 9:30 am and needs to be at port 3 by 11:00 am at the latest. A similar set of requirements need to be satisfied for the other two trips. The only aircraft available to the operator to satisfy all the requests has a home base at port 3 and therefore the aircraft must start and end the day at this port. The flight times and the turnaround times between the origin-destination (OD) ports appear in Table 3.

Table 2 Example problem trip requests

request (r)	origin(r)	destination(r)	earliest departure time (r)	latest arrival time (r)
r_1	2	3	09:30	11:00
r_2	3	1	15:00	16:30
r_3	1	3	09:20	10:30

Table 3 Flight time and turnaround time at the destination airport

Origin-Destination	Flight time [min]	Turnaround time at destination [min]
1-2	25	10
1-3	15	10
2-3	15	10

Figure 4 shows the individual aircraft time-event network with all possible nodes and the corresponding arcs connecting these nodes. Each node is represented by a node number followed by a set of numbers within the parenthesis as per the convention described in Section III.C.2. For instance, the first node $S(3, 10)$ states that the aircraft is in a standby mode at port 3 and is ready for takeoff at $t = 10$, i.e., 10 min past midnight. Similarly, the indirect loading node $IL(1, 560, 2, 600, 3, 3)$ (node number 10 in Fig. 4) states that the aircraft will satisfy request 3 indirectly by taking-off from port 1 at $t = 560$ (9:20 am), go to port 2, load the passenger from request 1 (aggregates demand to increase the load factor, leave port 2 at $t = 600$ (10:00am), and then go to its final destination to port 3, dropping off the passenger from both request 1 and 3 and waiting to serve request 2. The optimal aircraft path (shown in red) satisfies all the trip requests by maximizing the fleet-level profit. In the process of satisfying all the demand, the aircraft makes a total of five trips with two re-positioning (deadhead) flights. Figure 5 shows the movement of the aircraft during the day based on the optimal path of Fig. 4. The red lines represent the time window when the aircraft has no passengers on board and the green lines represent the time window when there are passengers on board the aircraft. The number next to the green line shows the number of passengers that are on board the aircraft.

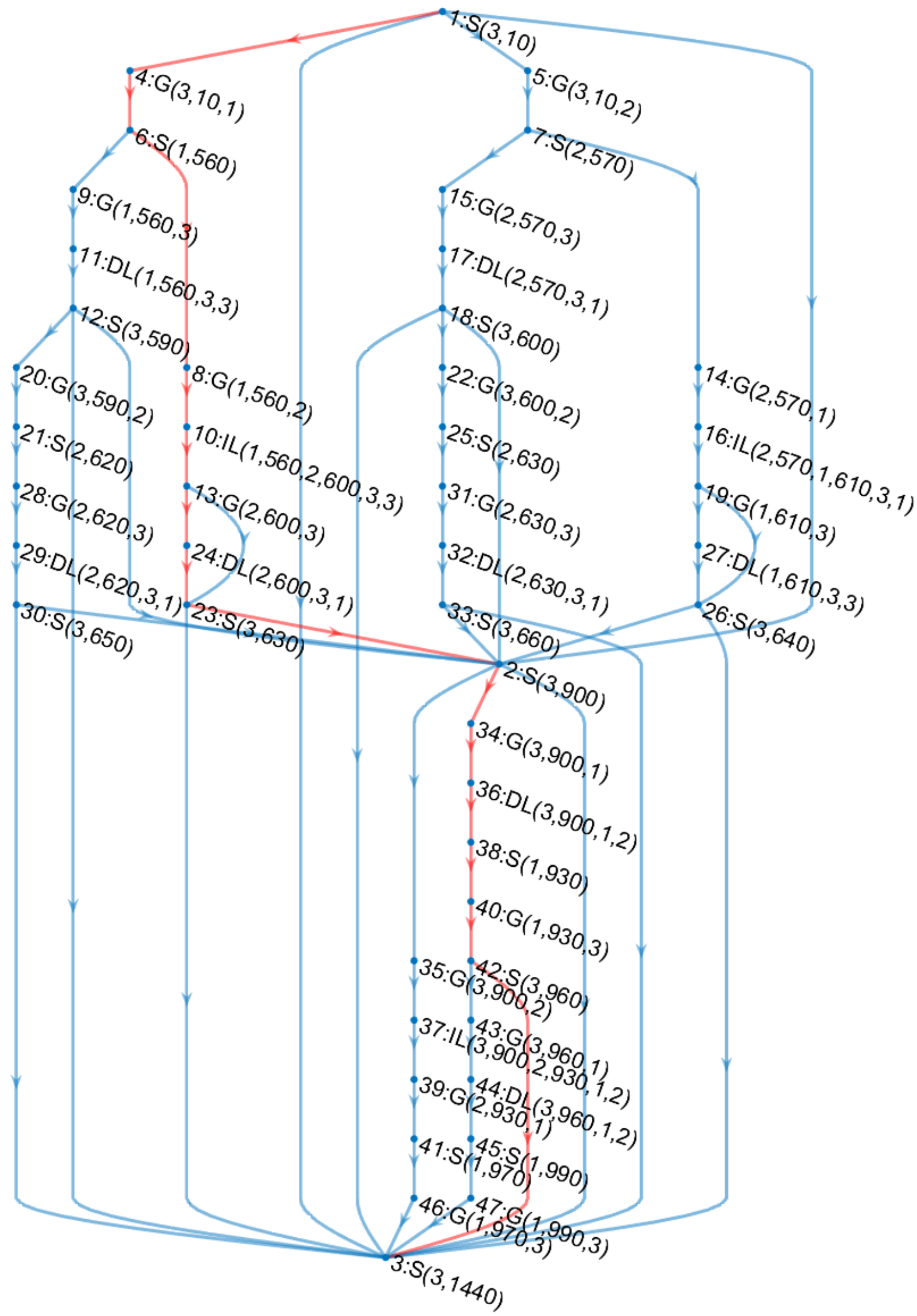


Fig. 4 Individual aircraft in the time-event network model with the optimal aircraft itinerary satisfying all the trip requests shown in red

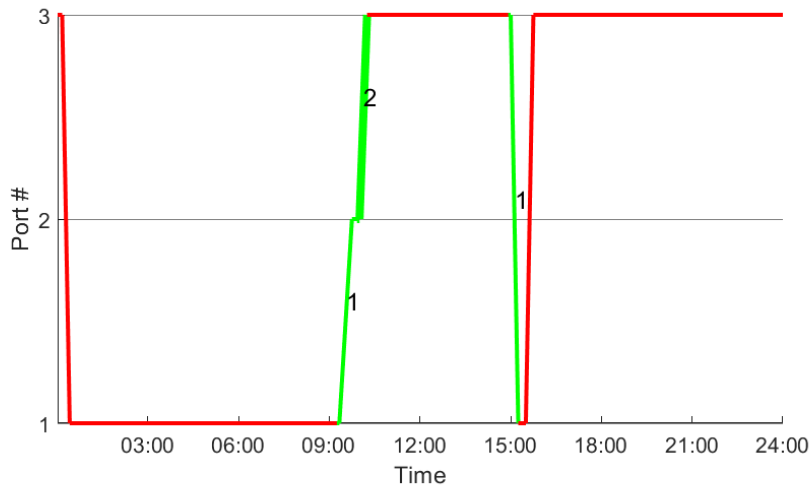


Fig. 5 Movement of the aircraft during the day satisfying the trip requests in time-space network

One of the challenges of using the original multi-commodity network flow problem formulation for a fleet-sizing application is that the original formulation assumes that the number of aircraft in the fleet is a known quantity. DayJet, the pioneer of the approach, had a proprietary online accept/reject system that only accepts a request if it can satisfy the request with the current number of aircraft in the fleet. This proprietary algorithm ensures that all the trip requests can be accommodated by the existing fleet size. However, in our case, the trip generation model generates trip requests solely based on the utility-based passenger model as discussed earlier and no prior information exists on how many aircraft are needed to satisfy the given demand. To obtain the number of aircraft needed, we followed a bi-level approach that first solves a demand maximization formulation for a given fleet size and then solves a profit maximization formulation that satisfies the maximum possible demand that can be met with the available fleet size.

In the first step, we solve the integer multicommodity network flow problem formulation with the objective function set to maximize the total demand, i.e., to satisfy maximum possible demand with the given fleet size. With the starting number of aircraft set to one, we continue to increase the number of aircraft in increments of one until 95% of the trip requests are satisfied. A demonstration of the approach appears in Fig. 6. For a ticket price set to $6.50 per passenger-mile (pax-mile), the operator may expect about 86 trip requests. With just one aircraft in the fleet, the operator is able to satisfy about 40% of the trip requests; however with four aircraft in the fleet, the operator is able to satisfy over 95% of the total trip requests.

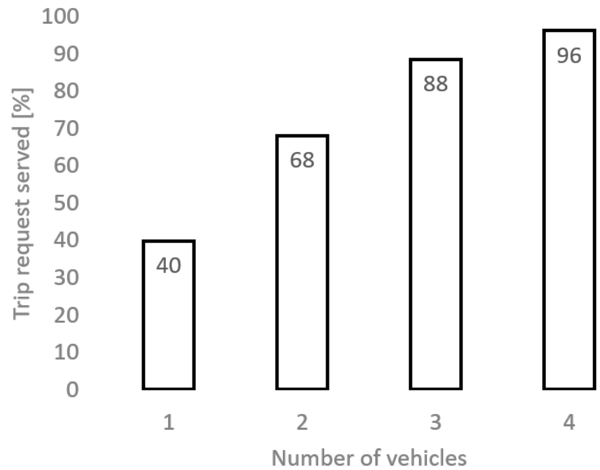


Fig. 6 Percentage of trip requests satisfied for a given fleet size

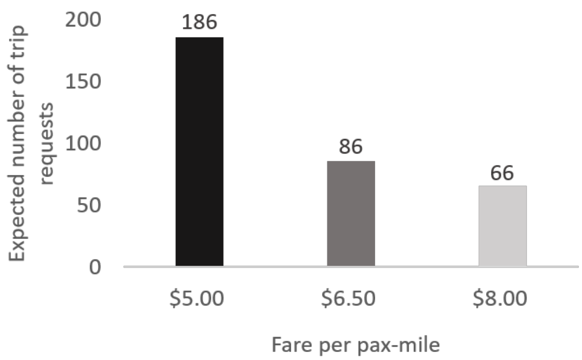
The fleet assignment solution from the first step, however, may be sub-optimal in terms of operating costs since the algorithm is not actively seeking to minimize the cost of operating the flights, and hence may result in a solution with unnecessary deadhead flights. To avoid this behavior, the problem is re-posed as a profit maximization formulation that maximizes the fleet-level profit of the operator subject to a constraint that ensures at least 95% of the total demand is met.

IV. Results and Analysis

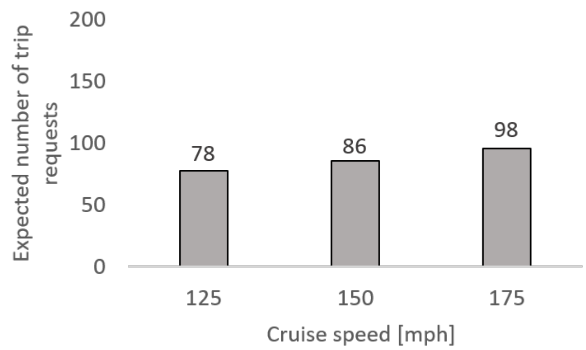
In this section, we present results that demonstrate the application of the dispatch algorithm to an airport shuttle air taxi service in the Atlanta metropolitan region. We first analyze the sensitivity of the demand to ticket price and aircraft cruise speed, followed by an assessment of fleet size requirements, and an exploration of the impact of fleet size on the fleet-level performance. Lastly, we carry out a sensitivity study to assess the effect of top-level aircraft characteristics on the fleet-level profit of the operator.

A. Demand sensitivities to ticket price and cruise speed

The demand, represented by the number of trip requests, is dependent on both the ticket price charged to the passengers and the aircraft cruise speed. These two parameters directly affect the results from the utility-based passenger choice model. A lower ticket price and higher cruise speed make the air taxi more appealing and increase the demand for the air taxi service. We performed the demand sensitivity studies for three ticket price and aircraft cruise speed values as appears in Fig. 7. Similar to the findings by Rothfeld et al. [34], we found that demand is more sensitive to the change in ticket price when compared to the change in the aircraft cruise speed. This insensitivity of aircraft cruise speed towards the passenger demand is likely a result of the fact that our example study is based on only a small geographic region in terms of flight distance, in which the maximum distance between any two ports (including the ATL airport) is approximately 40 miles. The time savings of using a faster aircraft (175 mph cruise speed) compared to the slowest aircraft (125 mph cruise speed) on this longest air taxi route is only approximately 5 minutes. A greater increase in demand based on using a faster aircraft would likely be more evident for a network with larger distances among the port pairs.



(a) Sensitivities to number of trip requests and fare



(b) Sensitivities to number of trip requests and aircraft cruise speed

Fig. 7 Expected number of trip requests due to different fares and aircraft cruise speed (baseline parameters include aircraft design range = 60 mi, cruise speed = 150 mph, seat number = 4, operating cost = $662 per hour, and fare = $6.50 per pax-mile)

B. Initial fleet size and fleet-level performance comparison: Helicopter and eVTOL

Fleet sizing is critical to the effective operation of a commuting service, particularly for a nearly or fully on-demand service whose success depends on timely operations. Operating with too few aircraft can result in a large number of trip requests being unfulfilled, making the service unreliable and undesirable. An excess of aircraft, however, may increase costs without providing a tangible benefit. In this section, the scheduling framework is applied to help understand the trade-offs among the number of air taxi aircraft, daily operating profit, and the ticket price.

Figure 8 shows the number of aircraft needed to satisfy at least 95% of the total trip requests for three ticket price options. The numbers in parenthesis show the percentage of the total trip requests that are satisfied across the three price points. A total of six 6-seat helicopters are needed compared to five 4-seat eVTOL aircraft for the $5.00 per pax-mile case. The reason for this is that the higher cruise speed of helicopter generates slightly higher number of trip requests and due to the spatial and temporal distribution of these new trip requests, an additional helicopter is needed to meet at least 95% of the total requests, despite its larger seat capacity.

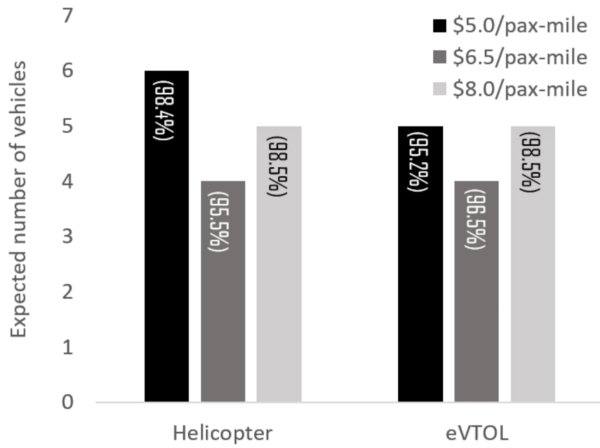


Fig. 8 Initial fleet size needed to satisfy at least 95% of the total trip requests

Figure 9 compares the expected daily fleet-level operating profit between the baseline helicopter and the eVTOL aircraft. Our analysis shows that a viable business case for an airport shuttle air taxi mission in the Atlanta metropolitan area is unlikely using the particular helicopter model, demand distribution, and port distribution at these ticket prices. The three ticket prices considered do not lead to a positive fleet-level profit given the high operating cost of the helicopter. On the other hand, there is a profitable business case with the eVTOL aircraft owing to its lower operating cost. On average, with our assumptions in this example study, it may be possible to obtain a daily profit of approximately $4,500* for the airport shuttle air taxi mission in the Atlanta metropolitan area, if operated at a price point of $5.00 per pax-mile.

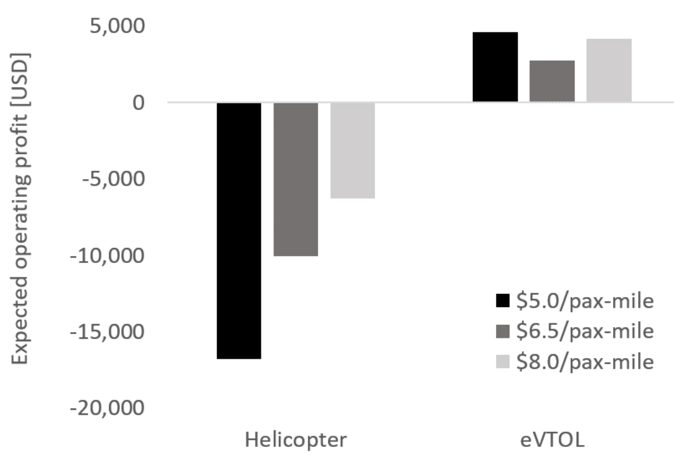
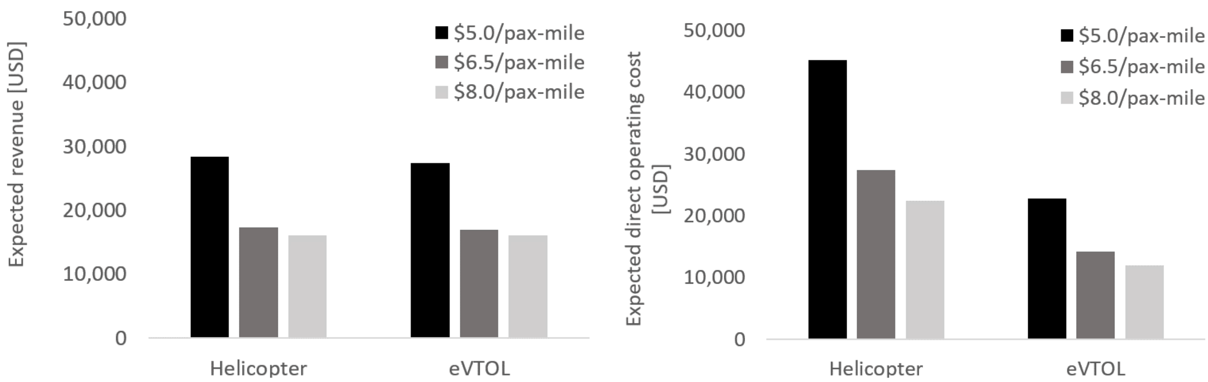


Fig. 9 Comparison of expected daily operating profit for three ticket prices

An interesting non-linear trend in the eVTOL case exists where both the $5.00 and $8.00 per pax-mile fares lead to a higher operating profit as compared to the $6.50 per pax-mile case. This shows that the operator may be able to

*The profit calculation depends on the operating cost of the vehicles presented in Table 1. It is likely that these operating costs do not consider some of the cost components that the operator may incur during real-world operations, and, hence, readers are cautioned that the profit numbers presented here are subject to significant uncertainty.

obtain equivalent profit by either operating at a lower price point to attract a larger market or target only fewer customers by charging a higher ticket price. This trend is explained by Fig. 10, which shows the daily fleet-level revenue and operating cost of both the helicopter and the eVTOL case. As the ticket price increases, both revenue and cost decrease; however, the relative decrease in revenue is smaller than the relative decrease in the cost between the prices \$6.50 and \$8.00 per pax-mile, leading to a slightly higher profit for the \$8.00 per pax-mile case. From Fig. 10, we also see that the larger seat capacity and higher design range of the helicopter do not contribute towards improving the fleet-level revenue of the operator.



(a) Fleet-level operating revenue

(b) Fleet-level operating cost

Fig. 10 Fleet-level revenue and cost comparison for the helicopter and the eVTOL aircraft

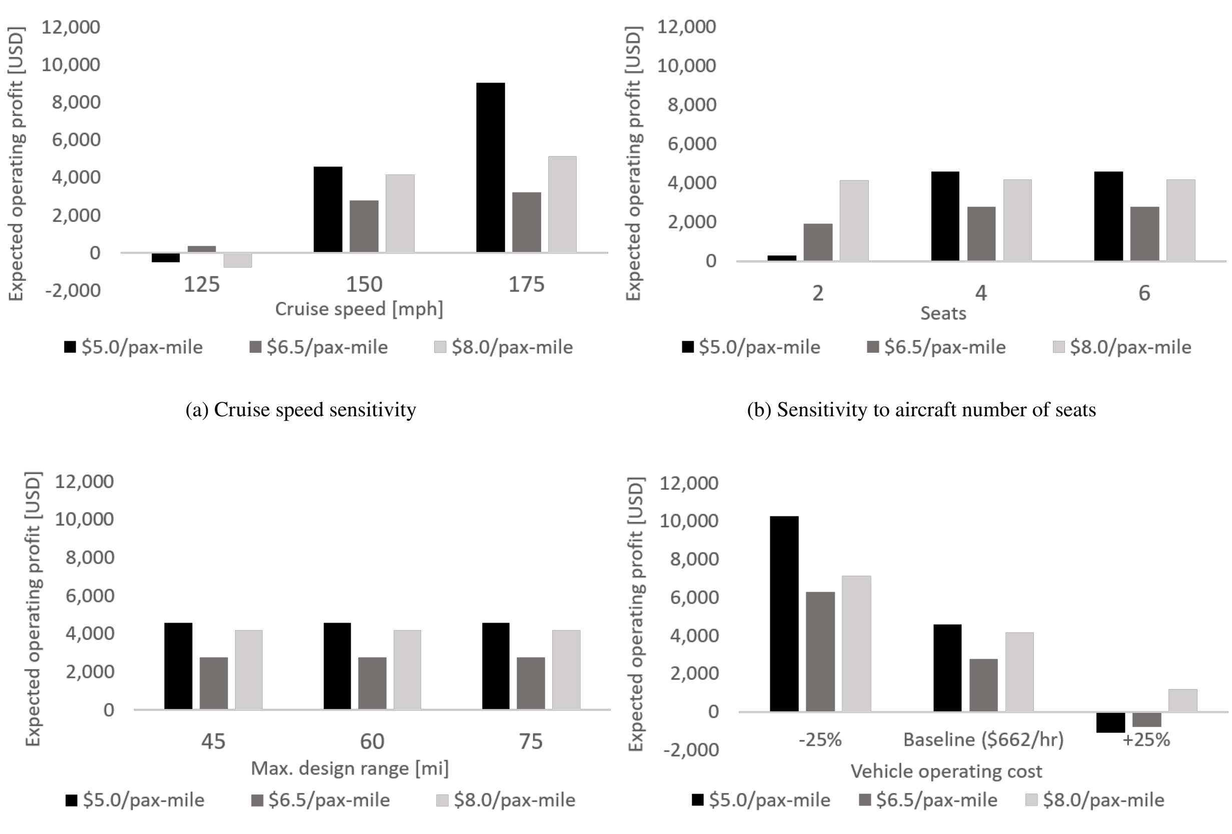
C. Sensitivity analysis: Payload, range, seats, and aircraft operating cost on fleet-level profit

In this section, we perform sensitivity studies to understand how top-level eVTOL aircraft characteristics affect the fleet-level objective of the operator , which we assume in this study to be daily operating profit. Figure 11 shows how different top-level air taxi aircraft configurations, defined by cruise speed, maximum design range, and number of seats on-board the aircraft, affect the daily profit of the operator assuming everything else remains constant. We also present a fourth case (see Fig. 11d) that shows how aircraft operating cost affects the overall profit of the operator. As expected, increasing the aircraft cruise speed increases the profitability of the operator, with the increase being more prominent at a fare of \$5.00 per pax-mile. Both lower ticket price and higher aircraft cruise speed contribute toward the generation of a large number of trip requests, thereby increasing the total number of trips and the fleet-level revenue.

Regarding sensitivity to the number of seats, the profit for the two-seat aircraft configuration is only affected at the \$5.00 per pax-mile ticket price. This is due to the need to have additional aircraft in fleet to satisfy the large demand at the lower price point, thereby increasing the total operating cost without improving the revenue. The increase in the total operating cost for this scenario is further justified by the fact that a two-seat aircraft allows very little room for efficient ride-sharing (only two seats are available to the passengers) and, hence, there is need to make many trips during the day to accommodate a large number of trip requests. It is important to note that the spatial and temporal location of the trip requests play an important role towards the algorithm's ability to efficiently do ride-sharing. If the trip requests are concentrated, both spatially and temporally, then a larger capacity aircraft will enable efficient ride-sharing, thereby improving profit margins.

The lower ticket price ($5.00 per pax-mile) yields a higher profit for the scenarios when the aircraft has a fast cruise speed (175 mph) or when the operating cost of the aircraft is low (25% reduction from the baseline case) and performs the worst (yields lower profit) when the size of the aircraft is small (2-seat), the aircraft operating cost is high (+25% increase from the baseline case), or the cruise speed of the aircraft is low (125 mph). The study reveals an interesting trade-off in which reducing the fare per pax-mile to $5.00 increases the revenue as more passengers will be able to afford the air taxi service; however, to accommodate this increase in trip requests, there is a proportionate increase in the fleet-level operating cost that brings down the overall profit, making it nearly equivalent to the $8.00 per pax-mile scenario.

The daily profit is unaffected by the design range of the aircraft for the metro Atlanta region because, as discussed earlier, the maximum separation between a pair of ports is only about 40 miles which is below the minimum aircraft design range (45 miles) option considered in this study.



(a) Cruise speed sensitivity

(b) Sensitivity to aircraft number of seats

(c) Design range sensitivity

(d) Vehicle operating cost sensitivity

Fig. 11 Impact of top-level aircraft design parameters on fleet-level profit

There also exists strong coupling factors among the aircraft-level characteristics and the aircraft operating cost are not captured in this study. For example, a 75-mile design range aircraft will require a larger battery and hence will be heavier and cost more to operate than a 45-mile design range aircraft. This increase in the cost may negate some of the increase in profit we estimate in this study. To effectively capture this coupling, we would require a credible aircraft sizing model, battery model, and cost model; all of which is beyond the scope of the current study. Further the absence of a battery recharge model limits our ability to accurately predict the recharging time of the aircraft between flights. Recharging time is presumed to be fixed at 15 minutes which corresponds to the aircraft turnaround time in our dispatch model.

The implication of adverse weather is also not considered in this study. Adverse weather would severely impact the operations of on-demand air taxi services, and there may be a need to provide an alternate mode of transportation (e.g. ,a ride guarantee) under such circumstances, which would further increase the operating cost to the operator. Furthermore, post COVID-19, it is not clear if remote work will become the new normal and, if so, how this trend would impact people's perception towards air travel. The trip generation model employed in our work does not consider any potential impacts of the pandemic on travel behaviour.

Lastly, the results presented in this paper showcase near-term, small-scale airport shuttle air taxi operations in the Atlanta region using eVTOL aircraft. Demonstration of large-scale, wide-spread usage of these vehicles, analogous to the Uber Elevate's [35] vision of operating thousands of vehicles in the urban region, would require implementation of a parallel local search strategy as an addition to the original multi-commodity network flow algorithm, described in Ref. [22], to make the approach computationally tractable. The implementation of the parallel local search strategy is beyond the scope of this paper.

V. Conclusion

The work described in this paper emphasizes the need for a credible operational model for UAM applications that can mimic, as accurately as possible, the day-to-day operation of the UAM operator. We build upon a dispatch algorithm previously developed for an on-demand air taxi service operator and apply the algorithm to an eVTOL airport shuttle air taxi service in the Atlanta area. The dispatch algorithm is augmented with a demand-based trip-generation model, aircraft model, and a strategy to identify the location of potential ports for UAM operations from existing infrastructure. The trip generation model leverages airport commuter and income information from ACS and ARC survey data and implements a utility-based decision model to identify individuals likely to utilize an airport shuttle air taxi service. Initial results demonstrate how the dispatch algorithm along with the other supporting models can help to identify the fleet-size needed to meet a given demand for an airport shuttle air taxi service. The results also show strong coupling among population density, income distribution, number of the aircraft in the fleet, ticket price, top-level aircraft requirements and vehicle operation cost on operator's profitability. These strong couplings suggest that a holistic modeling approach, such as the framework presented in this paper, is necessary to establish the operational parameters to achieve a viable business case for an airport shuttle air taxi service. Application of the framework to the Atlanta region showed the possibility of a positive cash flow for near-term small-scale initial operations of an airport shuttle air taxi service using a fleet size of five aircraft at a price point of $5 per passenger-mile and a 4-seat eVTOL aircraft with a 60-mile range and cruise speed of 150 mph, suggesting that there is an opportunity to achieve a viable business case for an airport shuttle air taxi service in the Atlanta region using eVTOL aircraft.

Acknowledgments

The work was partially supported by NASA under the award number 80NSSC18M0151. The authors would like to thank the anonymous reviewers for providing valuable feedback during the peer-review process.

References

[1] Kreimeier, M., Strathoff, P., Gottschalk, D., and Stumpf, E., "Economic Assessment of Air Mobility On-Demand Concepts," *AIAA Journal of Air Transportation*, Vol. 26, No. 1, 2018, pp. 23–36. doi:10.2514/1.D0058, URL `https://arc.aiaa.org/doi/10.2514/1.D0058`.

[2] Vascik, P. D., Hansman, R. J., and Dunn, N. S., "Analysis of Urban Air Mobility Operational Constraints," *AIAA Journal of Air Transportation*, Vol. 26, No. 4, 2018, pp. 133–146. doi:10.2514/1.D0120, URL `https://arc.aiaa.org/doi/10.2514/1.D0120`.

[3] Roy, S., Kotwicz Herniczek, M. T., German, B. J., and Garrow, L. A., "User Base Estimation Methodology for a Business Airport Shuttle Air Taxi Service," *AIAA Journal of Air Transportation*, 2020, pp. 1–11. doi:10.2514/1.D0216, URL `https://arc.aiaa.org/doi/10.2514/1.D0216`.

[4] Moore, M. D., Goodrich, K. H., Viken, J., Smith, J., and Fredericks, B., "High Speed Mobility Through On-Demand Aviation," *AIAA Aviation Technology, Integration, and Operations Conference*, Los Angeles, CA, 2013. URL `https://ntrs.nasa.gov/search.jsp?R=20140002448`.

[5] Antcliff, K. R., Moore, M. D., and Goodrich, K. H., "Silicon Valley as an Early Adopter for On-Demand Civil VTOL Operations," *16th AIAA Aviation Technology Integration Operation Conference*, 2016, pp. 1–17. doi:10.2514/6.2016-3466, URL `https://doi.org/10.2514/6.2016-3466`.

[6] Goyal, R., "Urban Air Mobility (UAM) Market Study," Tech. Rep. HQ-E-DAA-TN65181, NASA, November 2018. URL `https://ntrs.nasa.gov/citations/20190001472`.

[7] Roy, S., Maheshwari, A., Crossley, W. A., and DeLaurentis, D. A., "A study to investigate total mobility using both CTOL and VTOL-capable aircraft," *2019 Aviation Technology, Integration, and Operations Conference*, Dallas, TX, 2018, p. 3518. doi:https://doi.org/10.2514/6.2019-3518.

[8] Kohlman, L. W., and Patterson, M. D., "System-Level Urban Air Mobility Transportation Modeling and Determination of Energy-Related Constraints," 2018. doi:10.2514/6.2018-3677, URL https://doi.org/10.2514/6.2018-3677.

[9] Garrow, L. A., German, B. J., Mokhtarian, P., Daskilewicz, M., Douthat, T. H., and Binder, R., "If You Fly It, Will Commuters Come? A Survey to Model Demand for eVTOL Urban Air Trips," *2018 Aviation Technology, Integration, and Operations Conference*, 2018. doi:10.2514/6.2018-2882.

[10] Garrow, L. A., German, B., Mokhtarian, P., and Glodek, J., "A Survey to Model Demand for eVTOL Urban Air Trips and Competition with Autonomous Ground Vehicles," *AIAA Aviation 2019 Forum*, Dallas, TX, 2019. doi:10.2514/6.2019-2871, URL https://arc.aiaa.org/doi/10.2514/6.2019-2871.

[11] Martinez Zapico, J., Sun, D., and Crossley, W. A., "Assessing potential urban air mobility traffic density in a metropolitan area like Chicago," *AIAA Scitech 2021 Forum*, Virtual event, 2021. doi:10.2514/6.2021-1628, URL https://arc.aiaa.org/doi/10.2514/6.2021-1628.

[12] Rimjha, M., Hotle, S., Trani, A., Hinze, N., and Smith, J. C., "Urban Air Mobility Demand Estimation for Airport Access: A Los Angeles International Airport Case Study," *2021 Integrated Communications Navigation and Surveillance Conference (ICNS)*, Dulles, VA, 2021, pp. 1–15. doi:10.1109/ICNS52807.2021.9441659.

[13] Ha, T. H., Lee, K., and Hwang, J. T., "Large-scale multidisciplinary optimization under uncertainty for electric vertical takeoff and landing aircraft," *AIAA Scitech 2020 Forum*, Orlando, FL, 2020. doi:10.2514/6.2020-0904, URL https://arc.aiaa.org/doi/10.2514/6.2020-0904.

[14] Shihab, S. A. M., Wei, P., Shi, J., and Yu, N., "Optimal eVTOL Fleet Dispatch for Urban Air Mobility and Power Grid Services," *AIAA Aviation 2020 Forum*, Virtual event, 2020. doi:10.2514/6.2020-2906, URL https://arc.aiaa.org/doi/10.2514/6.2020-2906.

[15] Hamilton, T., and German, B. J., "Optimal Airspeeds for Scheduled Electric Aircraft Operations," *AIAA Journal of Aircraft*, Vol. 56, No. 2, 2018, pp. 545–555. doi:10.2514/1.C035051, URL https://arc.aiaa.org/doi/10.2514/1.C035051.

[16] Narkus-Kramer, M. P., Tejeda, J., Stouffer, V. L., Hemm, R. V., Trajkov, S., Creedon, J. F., and Ballard, B. D., "Net Present Value, Trade-space, and Feasibility of On-Demand Aircraft," *16th AIAA Aviation Technology, Integration, and Operations Conference*, Washington, D.C., 2016. doi:10.2514/6.2016-3302, URL http://arc.aiaa.org/doi/10.2514/6.2016-3302.

[17] Roy, S., and Crossley, W. A., "An EGO-like Optimization Framework for Simultaneous Aircraft Design and Airline Allocation," *57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, San Diego, CA, 2016. URL https://doi.org/10.2514/6.2016-1659.

[18] Roy, S., Crossley, W. A., Moore, K. T., Gray, J. S., and Martins, J. R. R. A., "Monolithic Approach for Next-Generation Aircraft Design Considering Airline Operations and Economics," *Journal of Aircraft*, Vol. 56, No. 4, 2019, pp. 1565–1576. doi:10.2514/1.C035312, URL https://doi.org/10.2514/1.C035312.

[19] Martin, C., Jones, D., and Keskinocak, P., "Optimizing On-Demand Aircraft Schedules for Fractional Aircraft Operators," *INFORMS Journal on Applied Analytics*, Vol. 33, No. 5, 2003, pp. 22–35. doi:10.1287/inte.33.5.22.19243, URL `http://pubsonline.informs.org/doi/abs/10.1287/inte.33.5.22.19243`.

[20] Munari, P., and Alvarez, A., "Aircraft routing for on-demand air transportation with service upgrade and maintenance events: Compact model and case study," *Journal of Air Transport Management*, Vol. 75, 2019, pp. 75–84. doi:10.1016/j.jairtraman.2018.11.005, URL `https://linkinghub.elsevier.com/retrieve/pii/S0969699717303538`.

[21] Espinoza, D., Garcia, R., Goycoolea, M., Nemhauser, G. L., and Savelsbergh, M. W. P., "Per-Seat, On-Demand Air Transportation Part I: Problem Description and an Integer Multicommodity Flow Model," *Transportation Science*, Vol. 42, No. 3, 2008, pp. 263–278. doi:10.1287/trsc.1070.0227.

[22] Espinoza, D., Garcia, R., Goycoolea, M., Nemhauser, G. L., and Savelsbergh, M. W. P., "Per-Seat, On-Demand Air Transportation Part II: Parallel Local Search," *Transportation Science*, Vol. 42, No. 3, 2008, pp. 279–291. doi:10.1287/trsc.1070.0228.

[23] Atlanta Regional Commission, "Activity-Based Model Calibration Report," 2017. URL `https://cdn.atlantaregional.org/wp-content/uploads/abm-calibration-report-2017.pdf`, retrieved 04 April, 2021.

[24] U.S. Department of Transportation, "Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis," 2016. URL `https://www.transportation.gov/sites/dot.gov/files/docs/2016%20Revised%20Value%20of%20Travel%20Time%20Guidance.pdf`, retrieved 07 November 2019.

[25] Robert T. Jantzen, and Klaus Volpert, "On the Mathematics of Income Inequality: Splitting the Gini Index in Two," *The American Mathematical Monthly*, Vol. 119, No. 10, 2012, p. 824. doi:10.4169/amer.math.monthly.119.10.824, URL `https://www.tandfonline.com/doi/full/10.4169/amer.math.monthly.119.10.824`.

[26] Gabaix, X., "Power Laws in Economics and Finance," *Annual Review of Economics*, Vol. 1, No. 1, 2009, pp. 255–294. doi:10.1146/annurev.economics.050708.142940, URL `https://www.annualreviews.org/doi/10.1146/annurev.economics.050708.142940`.

[27] "Uber Elevate Summit 2019: Live Stream Day 2 - YouTube," 2019. URL `https://youtu.be/E0Ub9Z8ifiQ?t=22176`, retrieved 29 September 2020.

[28] Microsoft Bing Map API Platform, "Overview | Distance Matrix API," 2019. URL `https://www.microsoft.com/en-us/maps/documentation`, retrieved 05 September 2019.

[29] Federal Aviation Administration, "Airport Data & Contact Information," 2019. URL `https://www.faa.gov/airports/airport_safety/airportdata_5010/`.

[30] Bureau of Transportation Statistics, "Airline On-Time Statistics, BTS," 2019. URL `https://transtats.bts.gov/ONTIME/`, retrieved 05 October 2019.

[31] Federal Aviation Administration, “Aircraft Registration Database,” 2018. URL https://www.faa.gov/licenses_certificates/aircraft_certification/aircraft_registry/releasable_aircraft_download/, retrieved 06 April 2021.

[32] Robertson, C. V., Shrader, S., Pendergraft, D. R., Johnson, L. M., and Silbert, K. S., “The role of modeling demand in process re-engineering,” *Proceedings of the Winter Simulation Conference*, IEEE, San Diego, CA, 2002, p. 1455. doi:10.1109/WSC.2002.1166418.

[33] Herring, J., Lurkin, V., Garrow, L. A., Clarke, J. P., and Bierlaire, M., “Airline customers’ connection time preferences in domestic US markets,” *Journal of Air Transport Management*, Vol. 79, No. 101688, 2019. doi:10.1016/j.jairtraman.2019.101688.

[34] Rothfeld, R., Fu, M., Balać, M., and Antoniou, C., “Potential Urban Air Mobility Travel Time Savings: An Exploratory Analysis of Munich, Paris, and San Francisco,” *Sustainability*, Vol. 13, No. 4, 2021. doi:10.3390/su13042217, URL https://www.mdpi.com/2071-1050/13/4/2217.

[35] Holden, J. and Goel, N., “Fast-Forwarding to a Future of On-Demand Urban Air Transportation,” Tech. rep., Uber Elevate, October 2016. URL https://www.uber.com/elevate.pdf/.