By Schedule or On-Demand? - A Hybrid Operational Concept for Urban Air Mobility Services

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Recent advancements in aircraft technology, aviation concepts, and airspace management made by the collective effort of industry, government, and academia have set the stage for a new transportation mode called Urban Air Mobility (UAM). Attracted by the potentially large commuter and personal air travel market, companies such as Uber and Airbus are working towards launching their UAM services in near future. As the type of fleet deployed and the nature of operations in UAM are inherently different than ground-based transportation, new concepts and procedures are currently being developed to ensure safety and efficiency of such operations which will take place alongside traditional aviation. Additionally, new models of operations management are needed to support strategic and tactical decision making of the service providers, such as scheduling, dispatching and fleet planning, for maximizing their preferred objectives. Although such models will be critical to the success of the enterprise, no research, to the best of our knowledge, has yet been conducted on developing these models. Taking into account the unique set of operational constraints associated with UAM services, this paper proposes mathematical models for commercial transport service providers to decide which type of scheduling to offer, how to dispatch the fleet and schedule operations, based on simulated market demand, such that profit is maximized. The optimal fleet size can also be determined using the models. Three different settings of services – on-demand service, scheduled service, and a mix of both services (hybrid operations) – are modeled for carrying out a comparative analysis of the different forms of operations based on metrics such as fraction of total demand served and profit.

I. Nomenclature

V = set of vertiports
N = set of nodes in the UAM network
A = set of arcs connecting nodes in the UAM network
G = UAM network
T = set of predefined "time slices"
K = set of eVTOL vehicles

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N' = set of all space-time (ST) nodes
A' = set of all ST arcs

Subscripts
i, j = nodes in G
(i, j) = arc in G
r,s = points in time that discretize analysis
h,i,j = ST nodes belonging to N'
k = vehicles in K

Parameters
q_{ij} = total potential demand from ST origin $i \in N'$ to ST destination $j \in N'$
e_{ij} = energy required for an eVTOL movement on ST arc $(i, j) \in A'$
E = battery capacity of eVTOLs
c_{ij} = cost of traversing ST arc $(i, j) \in A'$
β = slope of demand curve
C = eVTOL capacity
u_i = capacity of vertiport $i \in N$
t_{ij} = travel time from UAM node $i \in N$ to $j \in N$

Variables
E_i^k = energy of vehicle k at node $i \in N'$
p_{ij} = fare charged to travelers going from ST origin $i \in N'$ to ST destination $j \in N'$
x_{ij}^k = binary variable indicating whether eVTOL k is dispatched on ST arc $(i, j) \in A'$
x_i^k = binary variable indicating whether eVTOL k is stationed at node $i \in N$ at the initial state $t = 0$
d_{ij} = price responsive demand in ST arc $(i, j) \in A'$
C_{ij} = number of seats available for transporting passengers from ST origin $\mathrm{i} \in \mathrm{N}'$ to ST destination $\mathrm{j} \in \mathrm{N}'$
w_{ij} = number of passengers transported from ST origin $\mathrm{i} \in \mathrm{N}'$ to ST destination $\mathrm{j} \in \mathrm{N}'$
y_{ij}^k = number of passengers traversing ST arc $(i, j) \in A$ in eVTOL vehicle $k \in K$
z = total profit such that $z \in \mathbb{R}$

II. Introduction

It goes without saying that commuting in busy metropolitan areas, through dense traffic and frequent lights and stops, burns a wasteful amount of gas, time, and energy, often making it an unpleasant experience one wishes to avoid if possible. But, getting from point A to point B, along with the ride experience associated with it, is expected to dramatically improve soon, with respect to cost, time, and comfort, for commuters with the advent of Urban Air Mobility (UAM) - a promising new mode of transportation conceptualized to leverage unused airspace with helicopter-like aircraft called eVTOLs that stand for electric Vertical Take Off and Landing vehicles. Like helipads for helicopters, vertiports, placed strategically in the cities, will provide designated spaces to eVTOLs for takeoff and landing. UAM is envisioned to support a broad range of operations, such as emergency evacuations, search-and-rescue, news gathering, package delivery, weather monitoring, passenger transport, etc. With organizations including, but not limited to, NASA, Uber, Airbus, Volocopter, Aurora, Joby Aviation, and Kitty Hawk actively overcoming market feasibility barriers, aviation technology gaps, and operational challenges associated with the implementation and operation of UAM [1-7,20-22], these eVTOLs, designed to ferry passengers and goods on aerial virtual highways, are projected to hit the road, or in this case the air, soon. Several cities featuring a feasible infrastructure and an economically viable market for UAM - namely Dubai in United Arab Emirates, Sao Paulo in Brazil, San Francisco, Los Angeles, Boston, and Dallas-Fort Worth metroplex in USA, and some cities in New Zealand - have drawn the interest of government, academia and industry [1, 17-19].

A. Motivation

Previous research efforts on UAM focused on identifying and addressing the potential technical challenges associated with the implementation and operation of UAM network and vehicles in urban airspace: departure and arrival scheduling horizon and sequencing, trajectory management to ensure safe spatial and temporal separation, conflict resolution, integration with traditional flight operations in the national airspace, concept of operations, air traffic control, optimal required time of arrival, etc. [18-21]. Significant progress is being made to enable safe and efficient UAM operations alongside traditional aviation.

In light of these advances and findings, several companies are planning to provide on-demand aviation services in the near future. Although the concept of on-demand transportation service – a system that allows passengers to hail a ride whenever and wherever they desire – is still applicable in UAM, the nature of Operations Management (OM) and Fleet Management (FM) in three-dimensional airspace will be fundamentally different than that of ground-based transport services. Unlike most cars, eVTOLs will be powered by electric charge. Before any trip, it is necessary to ensure that the vehicle has the required amount of energy which will depend on a host of factors such as the flight profile, trip distance, journey time, etc. While fueling a car takes just a few minutes, a recharging time of around thirty minutes is expected for eVTOLs using high voltage charging stations at vertiports [1]. Another major difference arises from the fixed spatial coordinates of vertiports, which essentially fixes the number of routes or Origin-Destination (O-D) pairs the eVTOLs will shuttle about. These operational differences warrant the need for new OM decision support models, concerning route planning, fleet planning, vehicle dispatching and scheduling, to optimize the preferred objective of the service provider based on demand. To the best of our knowledge, no research has yet been conducted on developing these models. Taking this new set of operational constraints into consideration, this paper makes an attempt in this direction, by proposing a mathematical model for commercial UAM service providers to solve the eVTOL routing, dispatch, and scheduling problem based on simulated demand such that profit is maximized. The model can also be used for fleet planning to determine the optimal fleet size. Three different settings of services – on-demand service, scheduled service, and a mix of both services – are considered for carrying out a comparative analysis of the different forms of services based on metrics such as delay and profit.

B. Related Literature

An integral part of all logistics applications, the dispatch problem, which asks, in general, how best to assign employees, vehicles or other resources to customers, has been formulated and solved using different approaches in existing literature. Industries heavily reliant on dispatching range from transportation service providers, such as taxicabs, ridesharing companies, couriers, emergency services, etc., to home and commercial service providers for maid services, plumbing, pest control, electricians, etc.

The ambulance, or emergency vehicle in general, relocation and dispatching problem has been well-studied by researchers. Different techniques such as mathematical programming, heuristic based search algorithms, dynamic programming, etc. has been used previously to optimize performance metrics such as demand coverage, fleet size, average response time, and fraction of arrivals later than a certain threshold, etc. [22-29].

In the passenger transportation domain, vehicle dispatching strategies are designed based on trip-request models built using spatial-temporal passenger mobility data [30-36]. Utilization rate, number of rebalanced vehicles, idle mileage, mileage delay, demand served are some of the performance metrics that have been optimized using mathematical programming, receding horizon control, and heuristics [37-39]. In ridesharing applications, the objective is to find a pairwise assignment of vehicles and passengers such that customer waiting times and traveling mileage [40,41] are minimized.

Another problem closely related to dispatch is the scheduling problem. In fact, these terms have been used interchangeably in practice and in literature [43]. UAM scheduling process is expected to share similarities with that of airlines. The airline schedule development involves determining the frequency and timetable of the flight departures in each O-D market, subject to operational and fleet constraints [44]. An overview of popular fleet planning, route planning, and schedule development models used in the airline industry can be found in Ref. [44].

Henceforth, the terms vehicles and eVTOLs have been used interchangeably. The remainder of this paper is organized as follows. The next section presents our modeling approach. A discussion of the problem formulation and solution methods are given in sections IV and V respectively. Finally, the paper concludes with a review of the contributions made toward solving the UAM OM problem.

III. Problem Description

A. Problem Statement

From deciding which fleet type and size to deploy to choosing how many, when, and where to dispatch the vehicles during times of operation, commercial transportation-based companies planning to roll out UAM services would need to prudently make a number of strategic and tactical decisions to serve the commuter market with the goal of maximizing their preferred objective - profit. The focus of this paper is on developing models for vehicle dispatching and schedule planning, and solving them to find the optimal profit-maximizing decisions. Three types of scheduling models are considered: traditional, on-demand, or hybrid.

During UAM operations, the four possible decisions which can be made concerning any eVTOL at a vertiport at a certain time are: (1) dispatch it to another vertiport with passenger(s); (2) transfer it to another vertiport to serve demand there; (3) recharge it; and (4) delay it on the ground till the next decision-making instant of time. In other words, as there will be a certain number of vehicles at any given vertiport at each decision-making instant of time, the vehicle dispatching comes down to deciding how many vehicles to use for transportation to each of the other vertiports, how many to relocate to each of the other vertiports, how many to recharge, and how many to delay on the ground till the next time step. In the case of on demand UAM services, these decisions will be driven by both time-dependent stochastic route demand forecasts and real-time trip requests, whereas in traditional scheduling, the decisions are made based on only the route demand forecasts.

In this paper, ‘dispatching’ is used in the context of on-demand services to refer to deciding short-term vehicle allocations based on real time trip requests and the current demand forecast for the routes for a short time period into the future referred to as the look-ahead interval. On the other hand, ‘scheduling’ is defined as the process of developing timetables in advance for scheduling flight departures from the vertiports in the network. While dispatching needs to be executed on a running basis at each decision-making instant of time to account for the fluctuations in real time trip requests, scheduling is carried out only once ahead of time, which could be a few months or all the way up to a year, based on only the demand forecast. The ‘scheduling horizon’ or ‘planning horizon’ refers to the demand look-ahead interval, the time period of demand forecast used to make dispatching or scheduling decisions, which will be short for dispatching and long for scheduling. A hybrid UAM services, combining the best features of both on-demand and scheduled services, has been conceptualized to take one of four forms, varying across either vehicles or time or routes or across all three simultaneously. In the first type, referred to as hybrid-1 operations, some vehicles from the fleet will be designated to provide on-demand services while others will be used for scheduled services. In the second scenario, referred to as hybrid-2 operations, on-demand services will be offered during intervals with high demand forecast uncertainty and scheduled services during the other times. Providing on-demand services in some of the routes of the UAM network and traditional scheduled services in others is the defining concept of the third variant of hybrid operations – the hybrid-3 operations. The combination of hybrid-1, hybrid-2 and hybrid-3 operations results in the hybrid-4 operation, where the number of vehicles and choice of routes assigned for each service are allowed to vary throughout the day.

B. Modeling Approach

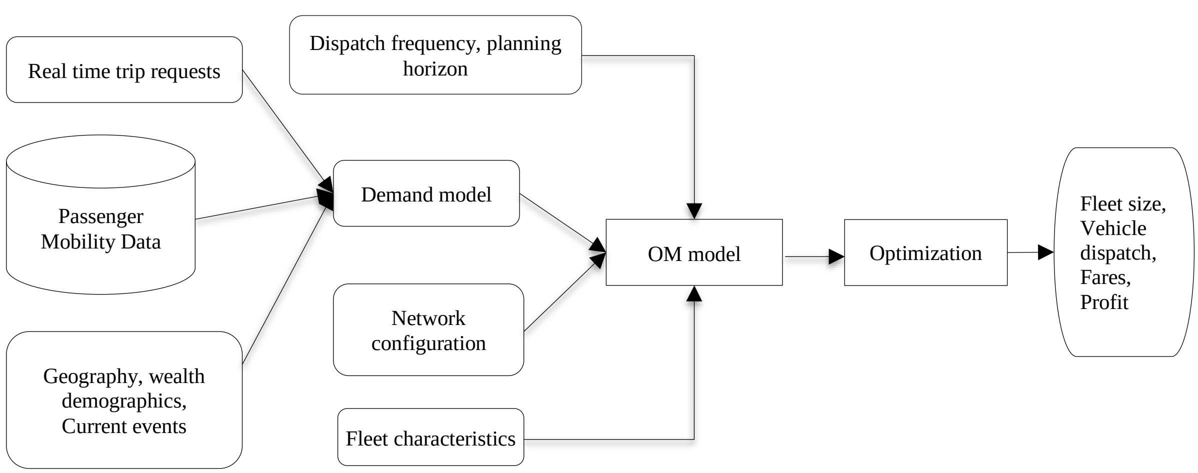

Fig. 1 The components of the on-demand OM model

The vertiport network, type of fleet, and temporal route demand distribution considered in this research problem are described below. As depicted in Fig. 1, these parameters are given as inputs to the on-demand OM mathematical model for determining the optimal fleet size, vehicle dispatch, and profit. In the case of traditional scheduled UAM services, the block diagram differs slightly with respect to the inputs and outputs. Firstly, demand is modeled using passenger mobility data and well-known calendar events without any real time trip requests. Secondly, the model needs to be solved only once ahead of the actual time of operation. Lastly, the vehicle dispatch output will be replaced by a profit-maximizing schedule. For hybrid UAM operations, the OM model will have to play the dual role of scheduler and dispatcher. In addition to the outputs shown in Fig.1, the model may also be used to compute the number of vehicles to allocate for each type of service as a function of time.

C. Network Model

An UAM network of 3 vertiports completely connected with each other through 6 distinct routes or O-D markets, as depicted in Fig. 2a), is considered as the testbed for this research. The nodes represent the vertiports and the bidirectional edges the two distinct O-D markets in each direction. In practice, this type of UAM network may be set up in any large metropolitan area like Dallas-Fort Worth (DFW) metroplex, Los Angeles, etc. and different facilities such as municipal airports, helipads, roofs of building, etc. may be used as vertiports. All vertiports are assumed to have adequate high voltage charging stations, maintenance facilities, parking spaces and takeoff and landing areas. Although, the routes are illustrated by straight lines, they may, in practice, take a different shape, such as piecewise linear or curve, comprising of a number of intermediate waypoints. Given the average route distances, travel times, and required charge amounts for each trip, the computation of optimal dispatch solutions can be carried out without knowing the exact route shapes, flight plans, altitude of vertiports, and departure and arrival procedures. All the routes are assumed to be 60-80 miles long, which is within the range of eVTOLs currently being developed. These O-D market distances are similar to the ones found in a study conducted in DFW metroplex [19]. Further description of the characteristics of eVTOLs enabling UAM service in the model network is given in the following section.

Expanding each node across time and geography results in the space-time (ST) UAM network illustrated in Fig. 2b), where the time axis has been sliced in intervals of 30 minutes. An extension of schedule maps previously used by airlines [44], the ST network provides a visual representation of the movement of vehicles across vertiports and time via two types of arcs: ground and flight arc. Vehicles remaining idle or parked or recharging at a vertiport for one or more time slices are represented by ground arcs, each of which have $e_{ij} < 0$. The remaining arcs, called flight arcs, represents the flow of vehicles from an origin ST node to a destination ST node. In a flight arc, $e_{ij} > 0$. Arrival times and departure times can be read off from the timescale by dropping vertical lines from the arc's start and end points in the ST network. The eVTOL turnaround times are assumed to be negligible in this research.

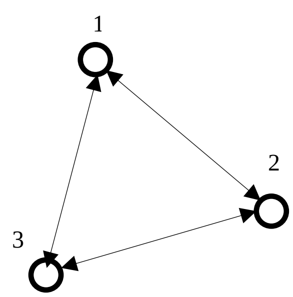

Fig. 2a) An example 3 vertiport network with complete route connectivity

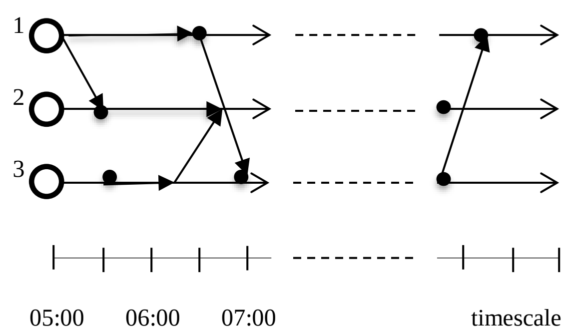

Fig. 2b) A ST network showing flight arcs and ground arcs for scheduling UAM services

D. Fleet Type

UAM vehicles are currently being developed by several companies, which include: Pipistrel, Embraer, XTI Aviation, Elytron, Eviation, Toyota, Workhorse, Detroit Aircraft Production, Yuneec Electric Aircraft DeLorean Aerospace, Urban Aeronautics LTD, Joby Aviation, EHang, Lilium Aviation, Carter Aviation and Mooney International, Evolo, Zee.Aero, Aurora Flight Sciences, Airbus A^3, Airbus & Italdesign, NASA, Kitty Hawk, Terrafugia, Bell Helicopter, etc. Electric propulsion, energy storage, and automation technologies are maturing at a rate that suggests all-electric eVTOLs will be available and economically viable by 2020 [1]. One of the key factors influencing the range, speed, and nonstop operational time of such eVTOLs is the specific energy densities of the batteries. The combination of the state-of-the-art battery and aviation technologies are expected to enable UAM flights carrying 4 people and spanning, at most, roughly 140 miles at an airspeed of around 170kts during cruise without needing to recharge [19,42]. This corresponds to an hour of continuous operation on full charge after accounting for charge consumption due to takeoff, climb, hovering and landing segments of the flight. Charging times of the batteries are expected to reduce to less than half an hour due to emerging charging capabilities [42]. The eVTOL operating cost per mile resulting from several factors – such as vehicle maintenance, infrastructure costs, piloting costs, recharging costs, capital expenses and other operating expenses – was estimated to be approach $0.64 in the near-term in [1]. Based on these information, a list of parameters and their corresponding values chosen for the purposes of this research is tabulated below.

Table 1 eVTOL characteristics

Model parameter	Value
eVTOL capacity	4
eVTOL range	100 mi
eVTOL cruise speed	160 mi/h
eVTOL nonstop operational time	1 h
eVTOL recharging time	30 min
Cost per vehicle mile	$ 0.64/mi

E. Demand Model

One of the key inputs to the OM model is the O-D market demands. This demand, which represents the number of passengers willing to travel in a given O-D market, will drive all operational decisions as it is the prime source of the revenue for the UAM service provider. Potential passenger demand for UAM services in Los Angeles and San Francisco Bay Area has been estimated in past studies using data sources such as helicopter charter services, census data, and consumer wealth data [42,45].

For the purposes of this research, market surveys and aggregate passenger behavior are currently being used to estimate temporal O-D market demands denoted by q_{ij}. Only point-to-point demand is considered in the OM model. The temporal O-D market demand distribution is estimated considering the hourly distribution given for each trip purpose (commute, family / personal, school / church, recreational and other) for the annual trips per start time from the Federal Highway Administration [46].

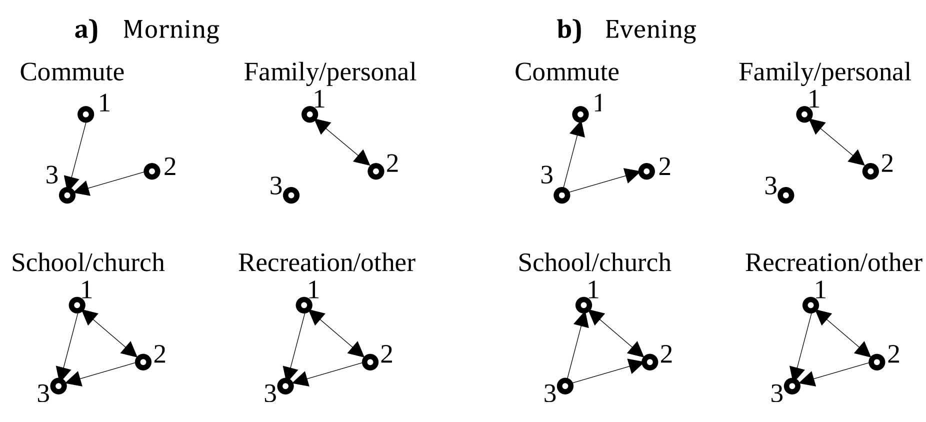

Fig. 3 O-D market demands per trip purpose a) morning b) evening

To distribute trips per purpose, the spatial distribution of activity location is set considering nodes 1 and 2 to be located on residential areas and node 3 on a central/downtown area. For instance, during the morning period, Fig. 3a) commuting trips are made from residential areas 1 and 2 to the central administrative area 3; Family/personal trips are made between the residential areas; school /church trips between residential areas and from residential node to the central/downtown node and lastly, for recreational and other purposes trips are made between all nodes. On the other hand, during the evening Fig. 3b) commuting trips are made from central/downtown node 3 to the residential areas 1 and 2; school/ church trips between residential areas and from central/ downtown to residential areas; at last trips made with recreational, family/personal and other purposes use a similar pattern as during morning period.

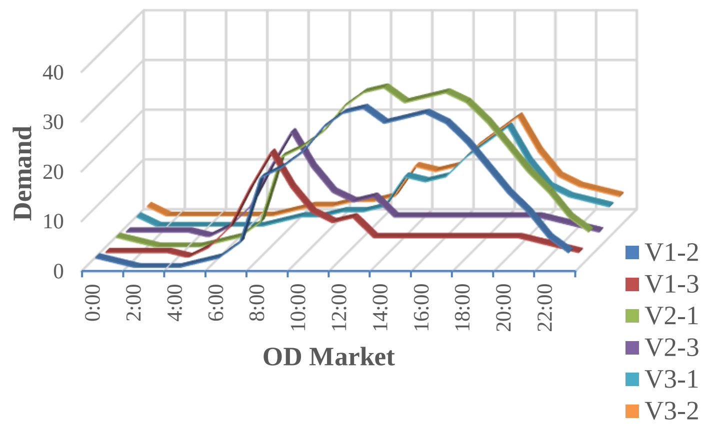

Fig. 4a) Plot of hourly demand forecast with respect to time for 9 O-D markets

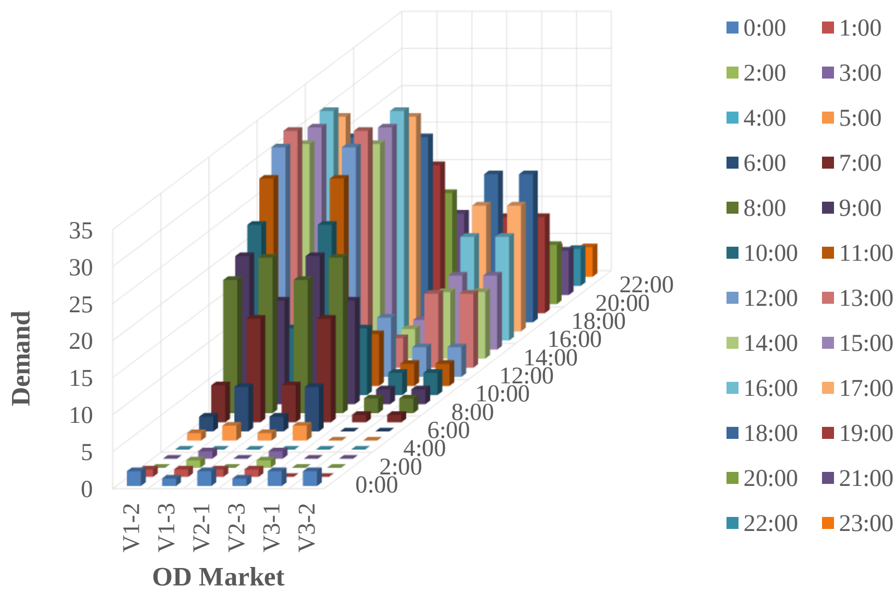

Fig. 4b) Column chart of hourly demand forecast of 9 O-D markets

Figures 3a) and 3b) depict the plot and column chart of non-zero values for the demand forecast for nine O-D markets at a given day of the week respectively. Demand is expected to vary differently throughout the day at each route depending on the flow directionality during the day.

F. Mathematical Formulation

A Mixed Integer Quadratic Programming (MIQP) approach has been employed to formulate the OM scheduling and dispatch problem at hand. The objective is to maximize profit over the scheduling horizon. As demand patterns typically repeat each week, the scheduling horizon is set to one week for the scheduling problem. For the dispatch problem, it is set to 3 hours. As the duration of trips and recharging periods are expected to take no longer than 30 minutes, the time of operation, $T = \{0,1,2, \ldots, |T|\} \in \mathbb{Z}$, is sliced into intervals of half an hour. A ST network, $G(N', A')$, like the one shown in Fig. 2b), is used for setting up the problem, where $A' = \{(i,j) = ((i,r),(j,s)) : i,j \in N; r,s \in T, s - r < t_{ij}\}$ and $N' = \{i = (i,r) : i \in N, r \in T\}$.

When the fleet size is fixed, binary decision variables can be specified for each vehicle-arc combination to indicate if a vehicle is present or not in a given arc. These variables are denoted by x_{ij}^k. Initial distribution of the vehicles at the vertiports are represented by x_i^k. For fleet planning, however, design variables need to be specified for each action-arc combination to represent the count of vehicles carrying out a certain action at a given arc. A description of the parameters and variables is given in the nomenclature section.

The objective function to be maximized is given in Eq. (1), which computes the total operational profit by subtracting the operational cost from the generated revenue for all arcs. Demand d_{ij} in any given ST arc fluctuates with fares p_{ij} as shown in Eq. (2), where q_{ij} represents the total potential demand in the ST arc. The number of passenger carrying seats available in any given ST arc is determined by the product of the capacity of eVTOLs and the number of eVTOLs dispatched on the given arc as shown in Eq. (3). Clearly, the number of transported passengers in the arc cannot be higher than the corresponding C_{ij} and d_{ij}. This is enforced by the constraints given in Eqs. (4) and (5). Although taking the minimum of C_{ij} and d_{ij} gives the optimal w_{ij}, this computation is not carried out directly as it would introduce a nonlinear term in the objective function. At the start of the operational period, all vehicles must be assigned to exactly one vertiport, as enforced by Eq. (6). At any ST node, the number of incoming vehicles must be equal to the number of outgoing vehicles. Equations (7) and (8) enforces the vehicle flow conservation at all ST nodes at the starting time and all other times in the scheduling horizon respectively. In the case of scheduled UAM services, the number of eVTOLs at each vertiport at the end of the scheduling period must match that at the beginning. This balance constraint is ensured by Eq. (9). Energy constraints are enforced in Eqs. (10), (11), and (12). At the first time instant, vehicles are assumed to have full energy. The first energy equation specifies that at the starting time the energy of a vehicle k at node n is full with charge E if the vehicle is present at the node. Otherwise, the energy of the vehicle at that node is zero. At all other times, the energy of a vehicle k at a node n is full if it arrived at that node by a horizontal recharging arc in the previous time slice, half full if it arrived at that node by a flight arc in the last time slice and a recharging arc in the second last time slice, and zero otherwise, as stated in Eq. (11). The subsequent equation specifies that a vehicle may be assigned to a flight arc only if its energy level exceeds or matches the required arc energy. Lastly, the vertiport capacity constraints, expressed in Eqs. (13) and (14), ensures that the number of vehicles at a vertiport at the starting time as well as at all other times does not exceed the vertiport's capacity.

Objective function

$$\max z = \sum_{(i,j)\in A'} p_{ij} w_{ij} - \sum_{k\in K} \sum_{(i,j)\in A'} c_{ij} x_{ij}^k \tag{1}$$

$$d_{ij} = q_{ij} - \beta p_{ij} \tag{2}$$

$$\forall (i,j) \in A'$$

$$C_{ij} = C \sum_{k\in K} x_{ij}^k \tag{3}$$

$$\forall (i,j) \in A'$$

Constraints

$$w_{ij} \leq d_{ij} \tag{4}$$

$$\forall (i,j) \in A'$$

$$w_{ij} \leq C_{ij} \tag{5}$$

$$\forall (i,j) \in A'$$

$$\sum_{i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} = 0 \in T} x_i^k = 1 \tag{6}$$

$$\forall k \in K$$

$$x_i^k = \sum_{j \in N' : (i,j) \in A'} x_{ij}^k \tag{7}$$

$$\forall i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} = 0 \in T, \forall k \in K$$

$$\sum_{i \in N' : (i,h) \in A'} x_{ih}^k = \sum_{j \in N' : (h,j) \in A'} x_{hj}^k \tag{8}$$

$$\forall h \in N' : h = (\mathscr{h}, r), \mathscr{h} \in N, r > 0 \in T, \forall k \in K$$

$$\sum_{i \in N' : (i,j) \in A'} \sum_{k \in K} x_{ij}^k = \sum_{k \in K} x_h^k \tag{9}$$

$$\forall j \in N' : j = (\mathscr{j}, \mathscr{s}), \mathscr{j} \in N, \mathscr{s} = |T| \in T,\ h \in N' : h = (\mathscr{j}, \mathscr{r}), \mathscr{j} \in N, \mathscr{r} = 0 \in T$$

$$E_i^k = x_i^k E \tag{10}$$

$$\forall i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} = 0 \in T, \forall k \in K$$

$$E_j^k = E x_{hj}^k + \sum_{i \in N' : (i,j) \in A', i = (\mathscr{i}, \mathscr{s}), \mathscr{i} \neq \mathscr{j} \in N, \mathscr{s} = r - 1 \in T} \frac{1}{2} x_{ij}^k \, x_{gi}^k E \tag{11}$$

$$\forall j \in N' : j = (\mathscr{j}, r), \mathscr{j} \in N, r > 0 \in T, \forall k \in K,\ h \in N' : h = (\mathscr{j}, r-1), g \in N' : g = (\mathscr{i}, r-2)$$

$$\sum_{j \in N' : (i,j) \in A'} x_{ij}^k e_{ij} \leq E_i^k \tag{12}$$

$$\forall i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} < |T| \in T, \forall k \in K$$

$$\sum_{k \in K} x_i^k \leq u_{\mathscr{i}} \tag{13}$$

$$\forall i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} = 0 \in T$$

$$\sum_{h \in N' : (h,i) \in A'} \sum_{k \in K} x_{hi}^k \leq u_{\mathscr{i}} \tag{14}$$

$$\forall i \in N' : i = (\mathscr{i}, \mathscr{r}), \mathscr{i} \in N, \mathscr{r} \in T$$

All three types of scheduling OM models are based on the mathematical problem formulation described above, but they vary in the set of constraints they impose, the scheduling horizon, and the number of times the problem needs to be solved or the computational cost.

G. Scheduler

In the case of traditional scheduled UAM service, the OM model used as the scheduler is solved only once with a possibly week long scheduling horizon without explicitly using the vertiport capacity constraint given by Eq. (13). The balance constraint given by Eq. (9) ensures that the vertiport capacity constraint is satisfied at the starting time. Only the demand forecasts for the ST arcs in the scheduling horizon is considered in the model to find the optimal solution. Hence, the performance of the scheduler will strongly depend on the accuracy of the demand forecasts. When the actual demand is different than the predicted demand, the vehicle distribution along the ST arcs may cause demand spill in some arcs due to insufficient number of vehicles assigned to that arc and poor vehicle capacity utilization in some arcs as a result of an excessively high seat availability in that arc. As the optimization problem is only solved once, the computational cost is low, raising no concern if the scheduler is ran sufficiently in advance to actual operations.

H. Dispatcher

In contrast, the OM model used as the dispatcher in the on-demand UAM setting is invoked at the start of each time slice with a much smaller scheduling horizon of 3-6 hours. Known real-time trip requests for the next two immediate time slices as well as the demand forecasts for future time slices in the scheduling horizon are leveraged to determine the optimal dispatch solution. All the constraints are imposed in the analysis except for the vehicle balance constraint at the last time instant given by Eq. (9) as the dispatcher is not obligated to follow a weekly schedule. Because the on-demand dispatcher takes into account real-time trip requests, it is expected to generate more profit than the scheduler albeit at the expense of higher computational cost which increases linearly with the time length of scheduling horizon and the number of eVTOLs and exponentially with the number of vetiports in the network. Hence, the successful implementation of the dispatcher in real world is subject to the availability of adequate computing power such that the optimal solution can be found in a matter of minutes.

I. Hybrid Scheduler-Dispatcher

Hybrid scheduling models utilize both a scheduler and a dispatcher to provide traditional scheduled and on-demand services respectively either in parallel or alternatively at different times of the operational period. In hybrid-2 operations, the dispatcher will be subject to an additional constraint to ensure that the vehicle distribution across the vertiports at the end of the on-demand period matches that at the beginning of the scheduled services period. These models offer solutions that are competitive with the one from the dispatcher, but for a much lower computational cost since the dispatcher is ran with a lower number of eVTOLs and/or vertiports. Hybrid-2 operations, however, do not offer any computational cost savings unless the scheduling horizon is reduced in the on-demand operational period.

IV. Solution Method

To solve the NP-hard optimization problems formulated in the preceding section, the quadratic programming solver Gurobi is currently being used. Numerical experiments are currently being conducted on a fully-connected 3 vertiport network with 20 eVTOLs. Performance metrics such as profit, fraction of total potential demand served, and passenger delays will be used for comparing the three types of UAM services.

Weekly demand forecasts have been obtained from the demand model described in section III. For any given ST arc, the number of real-time trip requests is obtained by sampling from a normal distribution with a mean set equal to the demand forecast of the given ST arc and a standard deviation ranging from 5-50% of the mean. The sample from the continuous distribution is then rounded to the nearest integer. A low standard deviation indicates good forecast accuracy and vice-versa. The standard deviation is varied to simulate varying degrees of forecast accuracy. A sensitivity analysis will be carried out on the value of the price elasticity or demand slope. Other model parameters, such as scheduling horizon, time discretization scheme, eVTOL characteristics and route connectivity, will also be varied to analyze the effect on the computational cost and profit. Increasing the scheduling horizon would make the problem more computationally demanding, but the model is expected to generate a more profitable solution.

Among the three types of services, the on-demand service is expected to score highest in the performance metrics followed by the hybrid service and traditional scheduled service. On the other hand, the scheduled service is expected to have the least computational cost, followed by the hybrid service and on-demand service. So, the hybrid services is expected to generate solutions that that balances well the performance metrics and the computational cost. It would be appealing to both time-sensitive and cost-sensitive passengers who prefer on-demand and scheduled services respectively.

V. Conclusion

The nature of UAM services is fundamentally different than other ground- or air-based transportation services, which warrants the need for new OM models for scheduling, dispatching, and fleet planning based on unique operational constraints and demand data. Towards that end, a MIQP problem has been formulated to support tactical decision making with the objective of maximizing profit. To estimate temporal O-D market demands, market surveys and passenger behavior data are currently being used. By combining on-demand and traditional scheduled services, a new form of service, called hybrid service, has been conceptualized, which may take one of four different forms. Three variants of the basic OM model are formulated, corresponding to the different types of possible UAM services, for performing a comparative analysis between them based on metrics such as profit, fraction of total potential demand served, and passenger delays. The next steps involve implementing the models and analyzing the results to verify our hypotheses. Afterwards, future work involves extending the current basic OM model to include stochastic demand, uncertainties in travel times, and ground segments of the UAM service to vertiports.

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