Journal of Air Transport Management 105 (2022) 102294

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Air taxi skyport location problem with single-allocation choice-constrained elastic demand for airport access

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ARTICLE INFO

Keywords:
Urban air mobility (UAM)
Advanced air mobility (AAM)
Air taxi
Skyport location
Revenue management
Hub location problem

ABSTRACT

Witnessing the accelerated commercialization efforts for air taxi services in across metropolitan cities, our research focuses on infrastructure planning of skyports. We consider design of skyport locations for air taxis accessing airports, where we present the skyport location problem as a modified single-allocation p-hub median location problem integrating choice-constrained user mode choice behavior. Our approach focuses on two alternative objectives *i.e.*, maximizing air taxi ridership and maximizing air taxi revenue. The proposed models in the study incorporate trade-offs between trip length and trip cost based on mode choice behavior of travelers to determine optimal choices of skyports in a city. We examine the sensitivity of skyport locations based on two objectives, three air taxi pricing strategies, and varying transfer times at skyports. A case study of New York City is conducted considering a network of 149 taxi zones and 3 airports with over 20 million for-hire-vehicles trip data to the airports to discuss insights around the choice of skyport locations in the city, and demand allocation to different skyports under various parameter settings. Results suggest that a minimum of 9 skyports located between Manhattan, Queens and Brooklyn can adequately accommodate the airport access travel needs and are sufficiently stable against transfer time increases. Findings from this study can help air taxi providers strategize infrastructure design options and investment decisions based on skyport location choices.

1. Introduction

Major cities around the world are currently struggling with a common problem: traffic congestion resulting from urban population growth and limited roadway capacity. Spikes in travel time across congested routes in a city can have unpleasant consequences, *e.g.*, not reaching the airport on time to catch a flight or delaying emergency vehicles in delivering a critical patient to a medical center. Such concerns have pushed the development of new higher speed transportation modes to avoid surface congestion altogether. eVTOL (electric vertical takeoff and landing) vehicles, also known as electric 'air taxis', are emerging as a promising option to improve urban mobility. While helicopter services have been around for quite a long time in various metropolitan areas, (*e. g.,* New York City, Los Angeles, São Paulo), the concept of urban air mobility (UAM) or advanced air mobility (AAM) for passenger transportation is focused on providing on-demand shared mobility using technology-efficient, less noisy, affordable, environmental friendly and potentially automated aerial vehicles (*i.e.,* air taxis). While air taxi services have not yet been launched in any major city, multiple industry groups (including air manufacturers, large private companies, and smaller start-ups) are actively working on projects to offer such services in the next few years (*e.g.*, Uber, Hyundai, Toyota, EHang, Volocopter, AirBus, Boeing, Lilium Jet, Terrafugia, Joby Aviation, Kitty Hawk and others).

In 2016, the transportation network company Uber released a comprehensive white paper (Holden and Goel, 2016) with a follow-up technical document (UberElevate, 2018) discussing their view on requirements of urban air taxis to make UAM feasible as an affordable solution to commuters. It is estimated that producing high volumes of safe and reliable air taxis would drive down passenger costs per trip (Hornyak, 2020; Holden et al., 2018). Furthermore, various technology requirements and regulatory steps associated with on-demand aerial mobility have been discussed by NASA (Holmes et al., 2017; Johnson and Silva, 2018); these include the use of distributed electric propulsion, concept vehicle design, power and energy requirements, noise and emission reduction, safety, and reduction in operation and energy costs. In past years, major brands and other eVTOL start-ups have made tremendous progress towards making the UAM concept a reality

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https://doi.org/10.1016/j.jairtraman.2022.102294
Received 21 September 2021; Received in revised form 13 August 2022; Accepted 15 August 2022
Available online 30 August 2022

(Downing, 2019; Glon, 2020). NASA signed Space Act Agreements with 17 companies in the aviation industry to conduct full field tests in urban environments. The UAM Grand Challenge (Hackenberg, 2019) by NASA is the first in a series of technology demonstrations aimed at evaluating different elements of UAM operations under various weather, traffic, and contingency conditions. A first version of an UAM Concept of Operations was released by the Federal Aviation Administration (Bradford, 2020) providing an initial road map on achieving high volume and safe urban air taxi operations. Such active interest and serious funding supporting air taxi projects is indicative of its (potential) widespread adoption in the near future.

Identifying the UAM market and understanding customers' preferences for on-demand eVTOL services is the primary consideration for planning UAM operations. As a preliminary assessment of the impact of air taxi services, several groups conducted surveys and analyses. For example, Rothfeld et al. (2018b) confirmed via simulations that the reduction in travel time may strongly influence the adoption of air taxi services. Another survey conducted by Airbus (Thompson, 2018) spanning three regions (New York City, Frankfurt and Shanghai) indicated that airport access/transfers are the best use case for UAM adoption by commuters. Similar investigation by other studies including Berger (2018); Goyal et al. (2018); Hasan (2019); Shaheen et al. (2018) suggests airport transfers as the most promising early market for UAM technology; this market could extend to include other urban commute trips as the density of demand for UAM increases with increasing fleet size and service area coverage (Goyal et al., 2018). Some recent studies that focus on the use case of airport access via UAM investigate business model options (Straubinger et al., 2021), economic feasibility (Lewis et al., 2021), demand estimation (Rimjha et al., 2021), and flight scheduling (Roy et al., 2022) of UAM services. The white paper by Uber (Holden and Goel, 2016) identified infrastructure development as a key challenge in enabling efficient UAM operations. In their paper, the term 'skyport' or 'vertiport' denotes the ground infrastructures required for air taxi operations (*i.e.*, boarding, alighting of passengers, eVTOL charging, take-off and landing operations). The air taxi service is multimodal in nature *i.e.*, the end-to-end trip would mainly involve use of ground transportation to and from the skyports (Goyal, 2018). Kreimeier et al. (2016) found that the willingness to pay for such on-demand aviation services is greatly affected by the first mile and last mile ground transportation distance. Thus, location of skyports based on travelers' choices might be a crucial factor in the overall adoption of this emerging mode of transportation.

Our study draws motivation from the key findings in the above studies. We focus on the problem of planning the ground infrastructure for air taxi services for airport access/transfers in an urban city. In particular, we incorporate travelers' preferences for UAM services to determine optimal skyport locations in an urban city with an objective of providing economically sustainable solutions to air taxi service providers. Given a large city with multiple candidate skyport locations, it is non-trivial to select a small subset as skyports that attracts all customer groups with different preferences, especially when the location choices and users' decisions of using air taxi services are closely interrelated.

1.1. Contribution

The broader market of mobility-on-demand and shared mobility has radically expanded in the global urban mobility sector over the past decade, along with an increasing interest in sustainable transportation solutions. Due to the rapid technological advancement (specifically regarding distributed electric propulsion and battery storage (Kuhn et al., 2011; Rezende et al., 2018), the concept of on-demand UAM using eVTOLs has captured much public attention and research interest in recent years as an energy-efficient, cost-effective, and competitive solution in an emerging market to alleviate traffic congestion in large cities and urban areas (Shamiyeh et al., 2017). It is important to identify and analyze the potential benefits, challenges and impact of UAM to successfully implement and integrate eVTOLs into the existing transportation ecosystem. One of the major factors closely tied to effective UAM operations is the ground infrastructure i.e., skyport locations in a city. Since the success of initial UAM networks would most likely determine the future demand and evolution of such services in cities, initial infrastructure planning and design of skyports is an important topic of research.

The contribution of this study is a proposed skyport location problem with elastic demand response and solution methodology that can be used by air taxi service providers for determining skyport locations in cities considering short term and long term price scenarios. The problem is a variant of the classic hub location problem (HLP) (Campbell, 1994b; O'Kelly, 1987). Given a set of fixed facilities (in our case airports) each serving various demand points, the location-allocation problem optimizes subsets of demand locations to be assigned to different transfer points (in our case skyports) for connection to multiple facilities (airports). We model the objective function in two ways leading to two variants of the skyport location problem *i.e.*, (1) revenue maximization problem and (2) ridership maximization problem. Our method optimizes the skyport locations considering travel costs, transfer times, and user demand for air taxis using a logit model. Typically such a formulation would be nonconvex due to the logit model constraint, but we show that under the single allocation model design we can formulate it as a linear model that can be solved using linear programming solution approaches. We analyze the sensitivity of skyport locations under three different pricing strategies (considering short-term and long-term price scenarios) and varying transfer times at skyports, to study how these parameters affect the choice of optimal skyport locations in a city. To be clear, this is an operational demonstration study; profitability analysis of air taxi services is beyond the scope of this study. Although the results are demonstrated for NYC, this method is fairly general and can be applied to other cities selected for air taxi operations. The findings of this study can provide insights that can be useful to manufacturing companies, policymakers, and shared mobility providers on how they may want to design the UAM infrastructure within an existing transportation network.

The remainder of this paper is organized as follows. Section 2 covers related work (including prior work on UAM infrastructure, and location models in the broader hub location framework) and highlights research gaps that motivated this study. The proposed methodology is described in Section 3. This is followed by Section 4 on the experiment and results and we conclude in Section 5.

2. Literature review

2.1. Prior work on eVTOL and research gaps

We first describe the recent industry research surrounding UAM and eVTOLs followed by prior work on eVTOL infrastructure planning.

Due to the rapid technological advancement, the concept of on-demand urban air mobility has captured much public attention and research interest in recent years. eVTOLs have been an area of active investment for various air manufacturers, service companies, and high-tech giants who have been pushing for its public acceptance. While the development of a safe and efficient eVTOL is necessary for implementation of UAM, various challenges and barriers to the future of UAM have been highlighted and addressed by companies, consulting services and regulatory agencies. Some of the key challenges include public acceptance, market space, airspace integration, safety, noise, emissions, air traffic management, regulations, certification, security, privacy, and pilot training (Deloitte Insights, 2019; Holden and Goel, 2016; Pelli and Riedel, 2020; Thipphavong et al., 2018; Thompson, 2018; Merkert and Bushell, 2020; Bradford, 2020; Grandl et al., 2018; Holmes et al., 2017; Shaheen et al., 2018). Additionally, one of the crucial factors identified was ground infrastructure (skyport) selection (Holden and Goel (2016)) to enable efficient air taxi operations and link multiple modes of urban transportation for a complete end-to-end trip (Lineberger et al., 2009). The multimodal structure of the air taxi service would include first mile access from origin location to the skyport, followed by boarding on the eVTOL, flight leg (take-off and landing) on a landing pad, de-boarding, and last mile transfer from the landing pad to nearest destination (Grandl et al., 2018; Lineberger et al., 2009). Due to limited space availability in urban cities, utilization of existing helipads as well as rooftops of high-rise parking garages or buildings for eVTOL operations is a topic of active interest (Duvall et al., 2019; Holden and Goel, 2016; Lineberger et al., 2019) targeted at reducing the air taxi infrastructure cost. A recent study highlighting current research and development in UAM (Straubinger et al., 2020) indicates ground infrastructure as a key determinant in successful adoption of this technology.

In the academic research community, prior work on eVTOL infrastructure selection focus on operational and space requirements for UAM infrastructure while discussing several layout options for skyports (Alexander and Syms, 2017; Vascik and Hansman, 2017a,b,c, 2018). These studies highlight various factors that contribute toward infrastructure planning of UAM (*e.g.*, population density, income levels, long commute times to work, congestion, tourism, and airport trips) and propose suitable locations for infrastructure (*e.g.*, existing helipads, rooftops of existing parking garages or high rise buildings, roadways, and open spaces in large intersections). Access to airports or other major transport hubs was ranked the highest in a study by Fadhil (2018) (in terms of importance of factors in assessing ground infrastructure station selection); a GIS-based analysis was used for studying skyport placement options. Lim and Hwang (2019) proposed selecting skyport locations by using a K-means clustering algorithm, and demonstrated results for the Seoul metro area. The clustering of trips to determine skyport locations (cluster centroids) was limited to only three major routes within the city. In addition, there was no explicit optimization algorithm to minimize the aggregate travel time based on the trips data, and the clustering approach was essentially a heuristic. Another similar study is that of Rajendran and Zack (2019). They also looked at skyport placement, starting first with a comprehensive analysis of the demand requirements for skyport siting before diving into analysis involving k-means clustering approach. The authors only looked at demand within 1 mile of each skyport and ignored the access/egress times in the computation of the switch to air taxi. Also, the air taxi eligible demand accounts for only the trips with air taxi travel times at least 40% less than the ground trip duration. These approaches do not exploit the spatial structures of multimodal paths (access, flight, and egress) connecting origins to destinations through different skyports located across a city. Considering the importance of access and egress ground transportation in the willingness to pay for such services (Kreimeier et al., 2016), it is essential to consider the trade-offs between the time savings and the service cost in the skyport planning process.

In order to understand the user demand due to such factors (*i.e.,* trip length and trip cost) and to be able to incorporate effects of such factors on user behavior in the planning process, a discrete choice based demand model is used. Based on multiple factors (individual specific, mode specific, attitudinal, social, psychological, and latent variables), various studies have used discrete choice models to understand travel behavior and user adoption of UAM services (Al Haddad et al., 2020; Balac et al., 2019a,b; Binder et al., 2018; Boddupalli, 2019; Fu et al., 2019; Garrow et al., 2019; Ilahi et al., 2019; Roy et al., 2021). Some studies have also looked into users' familiarity, wariness of new technology (Winter et al., 2020), user perceived benefits of flying taxis (Ahmed et al., 2021), and weather and ride related factors (Rajendran et al., 2021) affecting consumers' willingness to fly such services. A detailed market study by Booz-Allen and Hamilton, Inc. (Shaheen et al., 2018) estimated the potential demand of UAM in several cities in the United States, such as New York City, Los Angeles, Washington, D.c., San Francisco Bay area; we use their findings to calibrate the model in our case study. Using a demand model to incorporate traveler decisions and choices for UAM services, we propose a more general and principled optimization framework based on HLP for optimizing the locations of skyports in any given city. A survey by Thompson (2018) indicated that users were willing to pay more for air taxi services to avoid the negative consequences of ground transportation congestion leading to delays in airport transfers. Motivated by the survey results, we focus on airport access/transfers as a use case and optimize skyport locations for (1) maximizing air taxi ridership and (2) maximizing air taxi revenue. The advantage of modeling the skyport location problem using HLP structure with a mode choice model is that it is able to capture access costs to the skyports along with transfer costs of switching between modes, and optimize the locations based on the cost trade-offs to reflect user behavior.

2.2. Related work on hub location problem and choice-constrained optimization

The problem setup in our study has fundamental connections with HLP. Hubs serve as transfer or switching points in a many-to-many distribution network. The basic framework of the network HLP is to select the locations for hubs in order to serve N demand points accessing a facility in a network such that they fulfill an objective (*e.g.*, minimizing distance or travel time between origin-destination pairs in a network, maximizing profit from the hub facility). The potential locations for a hub facility are the trip origin locations (nodes) in the network.

The HLP can be applied to all areas where demand points need to be routed through some transfer locations or hubs (such that several demand points can be collected together at these hubs) for distribution to facilities. For example, this can be employed in an emergency aid system (Furuta and Tanaka, 2013) where patients can be transferred by ambulance to heliports (hubs) to be flown to hospitals (facilities). Usually this approach is used when the travel distance (or time) from a hub to the facility is comparatively less compared to traveling directly from demand points to the facility. Therefore, we use the concepts of HLP for locating multiple skyports to connect demand points in a city to multiple airports.

Depending on the objective, there can be three major variations to the HLP (Campbell, 1994a, 1996):

1. p-hub median (minisum),
2. p-hub center(minimax), and
3. covering problem,

where p is the number of hubs (typically an input parameter). In the p-hub median problem, the objective is to minimize the total transportation cost. This cost is defined in terms of the travel distance or the travel time from origin to destination. The p-hub median problem is NP-hard; even if the hub locations are fixed, the allocation part of the problem remains NP-hard (Kara, 1999). The problems which include service time are typically formulated as p-hub center or hub covering problems. While the objective in p-hub center problems is to minimize the maximum distance between origin and destination (O-D) pairs, the hub covering problem focuses on maximizing the service coverage.

The first mathematical formulations of HLP were introduced by O'Kelly (1987). In the HLP literature, this formulation is referred to as a single allocation p-hub median problem, where p is the number of hubs (typically an input parameter). The first linear integer programming formulation of this quadratic model was proposed by Campbell (1994b). Various linear models for HLP were later proposed by Ernst and Krishnamoorthy (1996) and Skorin-Kapov et al. (1996). The hub facilities in the HLP are categorized as uncapacitated (where there is no capacity restriction, Contreras et al., 2011; Klincewicz, 1996; Topcuoglu et al., 2005) and capacitated (where there is a limit to the maximum flow passing through a hub) (Aykin, 1994; Ebery, 2001). Several studies consider hub location under congestion effects, where the delay of accessing a hub is dependent on the flow entering the hub. Examples include de Camargo and Miranda (2012); Marianov and Serra (2003);

Özgün-Kibiroğlu et al. (2019). The reader may refer to Alumur and Kara (2008); Campbell et al. (2002); Farahani et al. (2013) for a comprehensive review on classification of various models and approaches to HLP. The classic HLP assumes the unit travel cost from a demand point to the hub is the same as that of traveling directly to the facility, whereas the unit travel cost between hubs (or from the hub to the facility (Berman et al., 2007)) is reduced by a discount factor (β *i.e.,* $0 < \beta < 1$). Some variants of HLP also allow direct connection from origin to the facility without being routed through a hub (Berman et al., 2007, 2008; Hosseinijou and Bashiri, 2012). In line with these assumptions, our setup considers use of ground transportation from demand points to skyports as well as for direct connections to airports, with air taxi connections (faster speed) from skyports to airports. The discount factor and direct connections in the HLP are accounted for in our skyport location model by mode specific travel costs in the multimodal setup.

Generic HLP problems are modeled mainly with an objective to minimize total network cost to satisfy all demand. However, when the decision to allocate demand via hubs is dependent on trade-off between various decision variables (as per user behavior), it is beneficial to define the model objective accordingly. For example, from a ridership point of view, it may be more advantageous to locate skyports such that the air taxi demand (*i.e.,* demand allocated to skyports) is maximized. Similarly, from a revenue perspective, the total fare collected from the demand going via skyports should be maximized. There are limited studies in the HLP literature focusing on maximization objectives. One variant of HLP with such objective is the hub maximal covering location model introduced by Campbell (1994b) where hubs try to maximize the demand coverage. Various extension to this model with different notions of coverage were investigated by Hamacher and Meyer (2006); Hwang and Lee (2012); Kara and Tansel (2003); Tan and Kara (2007); Wagner (2008). Alibeyg et al. (2016) introduced hub network design with profit and provided exact solution for such problems (Alibeyg et al., 2018). The profit calculation is based on total revenue obtained from captured flows minus the total cost of establishing hubs. Variations to this model setup can be found in Neamatian Monemi et al. (2017) and Taherkhani and Alumur (2019).

In terms of incorporating choice behavior in network optimization models, earliest works by Algers and Beser (2001); Andersson (1989, 1998) apply logit choice models to estimate buy-up and recapture factors at Scandinavian airlines system hubs. Marín and García-Ródenas (2009) incorporate user decisions as a constraint to model the rapid transit network for optimizing the location of the transit infrastructure. To address the additional complexity introduced by non-linear constraints (resulting from the use of a mode choice model), authors use piece-wise linear approximation for solving the network optimization model. The use of discrete choice models in revenue management in the context of airlines can be found in Talluri and Van Ryzin (2004) and in mixed integer linear programs in Paneque et al. (2021). These studies highlight the benefits and complexity of modeling user-based behavior in solving network optimization and revenue management problems under elastic passenger demand.

The skyport location problem in our study aims to determine the optimal locations of skyports for origin-destination (OD) pairs in a network, decide which subset of origin nodes to be served by the set of skyports to multiple destinations, and make allocation decisions based on user demand model. We formulate our skyport location problem with two different objectives: (1) maximizing air taxi ridership and (2) maximizing air taxi revenue. The hubs are treated as uncapacitated while we incorporate a mode choice model to include elastic user demand of going through the skyports (to multiple airports) based on trade-offs between different factors (influencing user decisions). Because the model is an uncapacitated HLP, the mode split is followed by a "single allocation" (de Camargo and Miranda, 2012) of the demand to the shortest path connecting the OD pair via a skyport. The is analogous to an all-or-nothing assignment in urban transportation modeling. By keeping the path selection deterministic to the shortest path with single allocation, we avoid the messier non-linearity if dealing with multiple (stochastic) route choice. Furthermore, the single shortest path means that path selection can be pre-processed for a given skyport location instead of having to incorporate path selection variables within the optimization model. To illustrate this fundamental difference, in a stochastic route choice (path endogenously selected) setting, flow would no longer be decided by a binary logit model between air taxi and ground taxi but would be non-linear as a choice between multiple routes and taxi. This is shown below, where x_k would be flow on path $k \in K_{rs}$ (needed for the objective) for OD rs, y_k is a binary decision on whether a path is open due to there being a skyport h open ($w_h = 1$), δ_{kh} is a path-skyport incidence parameter, A_k is the set of links on path k, u_k the travel time on path k, β is a calibrated travel time coefficient, β_{0rs} is the corresponding coefficient for taxi based on shortest path travel time $u_k^{'}$, and D_{rs} is the maximum demand.

$$
\begin{aligned}
x_k &= \frac{D_{rs} y_k exp(-\beta u_k)}{\sum_{k'} y_{k'} exp(-\beta u_{k'}) + exp(-\beta_{0rs} u_k^{'})} \\
y_k &\leq \delta_{kh} w_h, \forall k, h \\
y_k &\in 0, 1, \forall k \\
w_h &\in 0, 1, \forall h \\
x_k &\geq 0, \forall k
\end{aligned}
$$

In a single allocation model shown in the Methodology section below, we can avoid the non-linearity because only the shortest path will be chosen for an OD pair taking air taxi at a particular skyport. This allows us to determine flows per skyport and to select the flow that is minimal cost per OD pair.

3. Methodology

We first provide a high level overview of our approach used to formulate the skyport location problem in Section 3.1; this is followed by the formal problem formulation in Section 3.2.

3.1. High level overview

For a given city characterized by a discrete set of locations and multiple airports associated with it, the air taxi skyport location problem is formulated as a variant of the HLP. The skyport location problem in our study is defined as an optimization model with two alternative objectives *i.e.,* either maximizing air taxi ridership or maximizing air taxi revenue (not as a multi-objective problem but as two alternative optimization models). The number of skyports is a (budget) constraint in the formulation. Considering trip length and trip cost of the transportation mode as major influencing factors in our setup, we only consider a major subset of airport travelers (*i.e.,* regular taxi users) and estimate the behavioral mode shift of these travelers towards air taxis using a mode choice model (McFadden et al., 1973). The sensitivity of skyport locations to varying transfer time and trip cost is analyzed to study how these parameters affect the choice of optimal skyport locations.

- no capacity constraint is considered; our study is based on a subset of air taxi demand (*i.e.,* airport demand) with explicit demand response, hence the formulation is *uncapacitated* (reader may refer Vascik and Hansman (2019) that studies skyport capacity),
- *single allocation* refers to the assumption that the origin-destination demand is routed all-or-nothing according to a single shortest path going through a single hub or hub pair, as a consequence of the uncapacitated setting. This is a common assumption when congestion effects are negligible (i.e. taxi route choices only negligibly impact road congestion compared to passenger travel), where the only stochastic component is which mode the users will take,

- no fixed *infrastructure cost* is considered (number of skyports is considered as the budget constraint in our setup),
- conditions for *reduced travel cost* from transfer points to facilities and *direct allocation* of demand nodes to facilities (as in HLP) are both reflected in the mode choice model integrated in our skyport location problem that diverts a portion of the population of taxi passengers to air taxi,
- no *congestion effects* (see de Camargo and Miranda, 2012) are assumed at the skyports, and
- *existing landing space* for helicopters in airport zones are assumed to serve as landing zones for air taxis in our setup.

To be clear regarding the conditions above, we use the HLP model to design skyport locations that account for the access, egress and transfer costs allowed in the air taxi market. The trade-offs in these costs at different skyport locations are captured by an elastic demand function, modeled as a binary logit probability distribution applied at the OD level, to determine the expected market share of airport taxi users to choose air taxi (see de Dios Ortúzar and Willumsen, 2011; Mahmoodjanloo et al., 2020). The elastic demand integration distinguishes this work from other skyport design studies which have ignored the elasticity of demand. In the remainder of this paper we use the term hub and skyport interchangeably.

3.2. Problem formulation

In the following subsections, we first describe our setup with formal notation, decision variables, and then the optimization problem with associated constraints.

3.2.1. Setup

Consider a discrete set $\mathscr{L} = \{1, 2, 3, \ldots, N\}$ of locations spread across a given city. We consider trips from a location $i \in \mathscr{L}$ to an airport $j \in \mathscr{J}$, where $\mathscr{J}$ is the set of airports in the city (discrete set of size $N_{dest} \geq 1$). In other words, we only focus on trips which have an airport in set $\mathscr{J}$ as their destination.

Two main modes of commute to airports are considered, *i.e.,* direct ground service (ground taxi) and aerial service (air taxi), as we assume the air taxis would primarily compete with ground taxis. As such, the taxi user population is used as the market from which users may shift to air taxi. Given such alternatives, we assume an individual's choice of travel mode (to a destination) is greatly influenced by trip length and price of the trip made by the mode (Fu et al., 2019). Since the pricing of air taxi services would be adjusted based on market conditions over time, the focus is not on the pricing decisions but how user responses to such decisions affect the choice of skyport locations. Therefore, in terms of air taxi price, the estimates by Uber (Dickey, 2018; Holden and Goel, 2016) are assumed. Based on these values, we consider three different price scenarios for our analyses:

- Short term (ST): Air taxi price is \$5.73 per passenger mile
- Medium term (MT): Air taxi price is \$1.86 per passenger mile
- Long term (LT): Air taxi price is \$0.44 per passenger mile

In our setup, the originating airport demand at each origin node is fulfilled either via a skyport or via direct ground transportation (as shown in Fig. 1); the proportion distribution depends on the mode choice decisions by users based on attributes such as trip length and trip cost to the destination airport as per commute options. Travelers' decisions to choose air vs ground taxi from an origin to a destination (OD) are reflected by a binary logit model (as described in Section 3.2.5); each OD pair has one shortest path for the air taxi model for which attributes are computed using the parameters described below.

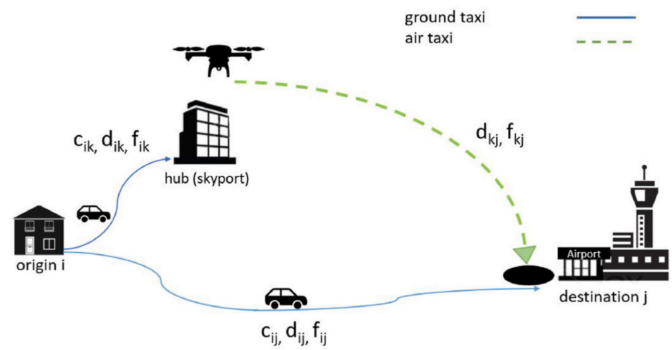


Fig. 1. Allocation of demand from an origin i to destination airport j as per commute options and decision variables. The demand can be satisfied via a single skyport k (*i.e., i* allocated to k) using air taxi and via direct ground transportation (i to j) using ground taxi. c_{ab} indicates trip time from point a to point b, while d_{ab} is the corresponding distance, and f_{ab} denotes the associated trip fare.

3.2.2. Decision variables

The decision variables are defined in Equations (1) and (2).

$$y_k = \begin{cases} 1 & \text{if location } k \text{ is a skyport,} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

$$x_{ikj} = \begin{cases} 1 & \text{if demand at origin } i \text{ for destination } j \text{ is satisfied via a skyport at location} k, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

3.2.3. Parameters

The set of parameters to the proposed optimization problem (as shown in Fig. 1) are defined as follows:

- $c_{ik} \triangleq$ ground transportation (access) trip time (minutes) between origin i and candidate skyport k with $i, k \in \mathscr{L}$ and $c_{ik} \geq 0$
- $d_{ik} \triangleq$ ground transportation (access) trip distance (miles) from origin i to candidate skyport k with $i, k \in \mathscr{L}$ and $d_{ik} \geq 0$
- $c_{ij} \triangleq$ direct ground transportation trip time (minutes) from origin i to destination j with $i \in \mathscr{L}, j \in \mathscr{J}$, and $c_{ij} \geq 0$
- $d_{ij} \triangleq$ direct ground transportation trip distance (miles) from origin i to destination j with $i \in \mathscr{L}, j \in \mathscr{J}$, and $d_{ij} \geq 0$
- $d'_{kj} \triangleq$ ground trip distance (miles) from node k to destination airport j with $k \in \mathscr{L}, j \in \mathscr{J}$, and $d'_{kj} \geq 0$
- $d_{kj} \triangleq$ aerial distance (miles) from candidate skyport k to airport j with $k \in \mathscr{L}, j \in \mathscr{J}$, and $d_{kj} \geq 0$
  - [•]d_{kj} is a function of d'_{kj} as explained in Section 4.1.3
- $f_{ij} \triangleq$ fare associated with direct ground transportation trip (USD[1]) from origin i to destination j with $i \in \mathscr{L}, j \in \mathscr{J}$, and $f_{ij} > 0$
  - [•]f_{ij} is a function of c_{ij} and d_{ij} as explained in Section 4.1.3

[1] United States Dollar.

- $f_{ik} \triangleq$ fare associated with access ground transportation trip from origin i to candidate skyport k (USD) with $i, k \in \mathscr{L}, f_{ik} \geq 0$
  - [•]f_{ik} is a function of c_{ik} and d_{ik} as explained in Section 4.1.3
- $f_{kj} \triangleq$ fare associated with air taxi commute (USD) from candidate skyport k to destination j with $i \in \mathscr{L}, j \in \mathscr{J}, f_{kj} > 0$
  - [•]f_{kj} is a function of d_{kj} as mentioned in Section 3.2.1
- $f_{ikj} \triangleq$ cost associated with end-to-end air taxi trip (USD) from origin i to destination j via candidate skyport k with $i \in \mathscr{L}, k \in \mathscr{L}, j \in \mathscr{J}, f_{ikj} \geq 0$
  - [•]$f_{ikj} = f_{ik} + f_{kj}$
- $D_{ij} \triangleq$ demand originating from i to destination airport j with $i \in \mathscr{L}, j \in \mathscr{J}$, and $D_{ij} \in \mathbb{N} = \{1, 2, 3, 4, 5, \ldots\}$
- $p \triangleq$ number of skyports

3.2.4. Incorporating transfer times

UAM use is a multimodal trip (shown in Fig. 2). This involves some amount of time (*i.e.,* additional travel cost) to transfer to and from the skyports.

- *transfer1* (α_1): this refers to the time required to switch between ground transportation to air taxi along with access time to the take off zone of the skyport; we consider an equivalent in-vehicle (ground transportation) time as α_1,
- *transfer2* (α_2): this refers to the last mile transfer via ground transportation from a landing zone (*e.g.,* existing helipad located nearest to the destination airport) to the destination airport terminal.

In order to test the sensitivity of optimal hub locations and the demand for those hubs to transfer times, we include a transfer cost in the air taxi service. This is reflected in the mode choice model to account for the impact of transfers on users' behavior. We essentially consider a transfer cost (t_k) associated with the total transfer time ($\alpha_1 + \alpha_2 \geq 0$); this value is captured in the total air taxi cost (f_{ikj}) as shown in Eq. (3).

$$f_{ikj} = f_{ik} + t_k + f_{kj} \tag{3}$$

3.2.5. Choice constraints

We integrate user mode choice behavior into our optimization problem. The demand for air taxis is governed by a mode choice model, which determines the split of each OD demand to air taxi. Since we consider a single allocation uncapacitated skyport location problem (which is a common problem in the literature: *e.g.,* Contreras et al., 2011; Klincewicz, 1996; Topcuoglu et al., 2005), this air taxi demand is then assigned to a single shortest path that depends on which skyport location is selected. This way, user choices are explicitly taken into account to include elastic user demand of going through the skyports to multiple airports.

We only consider airport travelers using regular taxi as the primary competition for air taxi and estimate the behavioral mode shift of these travelers towards air taxis using a binary logit model (McFadden et al., 1973). A binary logit model involves defining an utility function for individual n, associated with alternative $a(U_{n,a})$ from a binary choice set $\mathscr{A}$. The utility can depend on the attributes of alternatives and individual characteristics. $U_{n,a}$ has two components *i.e.,* a deterministic component ($V_{n,a}$) for the observable portion of the utility, and an error component ($\epsilon_{n,a}$) assumed to be Gumbel distributed.

We adopt findings available from existing studies (and surveys) on user behavior in NYC to define the utility functions of ground taxi and air taxi in our binary logit model. A detailed market survey on UAM by Booz-Allen and Hamilton, Inc. (Shaheen et al., 2018) estimates a logistic regression model considering multiple individual and alternative specific variables (including UAM trip distance and UAM trip cost) to predict users preference for air taxi as a commute mode in NYC. The model is based on a stated preference survey of willingness to use UAM and does not consider any other alternative modes. Another study by Ma et al. (2017) considers trip cost and trip time as influencing variable to estimate a mode choice model comparing taxi (or for-hire-vehicles) along with other modes for airport access in NYC.

Both the above mentioned demand studies (Ma et al., 2017; Shaheen et al., 2018) use survey data from NYC (which is our study area). We define the utility components of the alternatives in our binary logit model as shown below.

- Ground taxi: Trip time (minutes) and trip cost (*i.e.,* taxi fare in USD)
  - $V_{n,groundtaxi}$: f(c_{ij}, f_{ij}) (parameters as in Section 3.2.3)
  - $c_{ij}, f_{ij} \mapsto \beta_{TTgroundtaxi} \times c_{ij} + \beta_{COgroundtaxi} \times f_{ij}$

  where $\beta_{TTgroundtaxi} = \frac{1}{min}$ and $\beta_{COgroundtaxi} = \frac{1}{USD}$

- Air taxi: UAM trip distance (air miles) and UAM trip cost (*i.e.,* air taxi fare in USD)
  - $V_{n,airtaxi}$: $f(d_{kj}, f_{ikj})$ (parameters as in Section 3.2.3)
  - $d_{kj}, f_{ikj} \mapsto \beta_{TLairtaxi} \times d_{kj} + \beta_{COairtaxi} \times f_{ikj}$

  where $\beta_{TLairtaxi} = \frac{1}{miles}$ and $\beta_{COairtaxi} = \frac{1}{USD}$

Based on the above, the utility functions of ground taxi and air taxi are shown in Eqs. (4) and (5):

$$\begin{aligned} U_{n,groundtaxi} &= V_{n,groundtaxi} + \epsilon_{groundtaxi} \\ \Longrightarrow U_{n,groundtaxi} &= \beta_{TTgroundtaxi} \times c_{ij} + \beta_{COgroundtaxi} \times f_{ij} + \epsilon_{groundtaxi} \end{aligned} \tag{4}$$

$$\begin{aligned} U_{n,airtaxi} &= V_{n,airtaxi} + \epsilon_{airtaxi} \\ \Longrightarrow U_{n,airtaxi} &= \beta_{TLairtaxi} \times d_{kj} + \beta_{COairtaxi} \times f_{ikj} + \epsilon_{airtaxi} \end{aligned} \tag{5}$$

Based on the studies by Shaheen et al. (2018) and Ma et al. (2017), we assume the values for $\beta_{TTgroundtaxi} = 0.0313$, $\beta_{COgroundtaxi} = -0.0125$ (Ma et al., 2017), and $\beta_{TLairtaxi} = 0.018$, $\beta_{COairtaxi} = -0.0213$ (Shaheen et al., 2018) respectively. For a binary logit model, there is typically a single alternative specific constant (ASC) representing differences between the two alternatives that are not captured by any of the variations

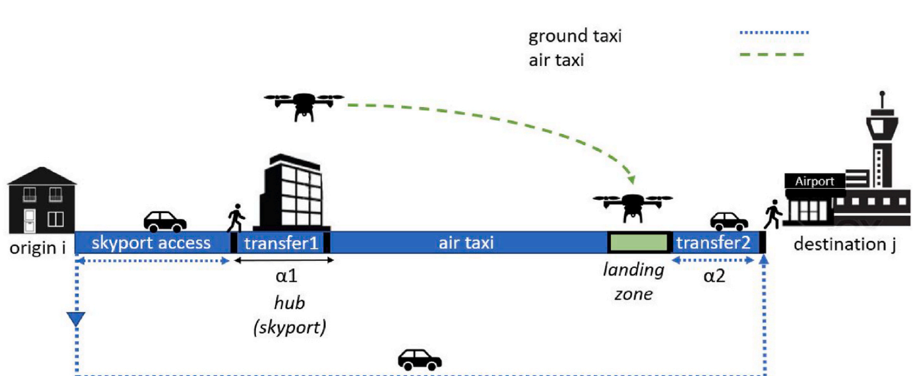


Fig. 2. Multimodal structure of air taxi service from origin i to destination airport j via a skyport k involves ground access, transfer1, air taxi, and transfer2.

characterized by the attributes. For air taxis and ground taxis, these differences may include: average population concerns about flying, the interest in trying an emerging technology, the net difference in inconvenience not captured by attributes, etc. The model from Shaheen et al. (2018) has an ASC = 1.25, which assumes that, without any other factors considered, 78% of users of that survey would be willing to make a trip via UAM. However, their model is for willingness to make a trip via UAM, absent of any other alternative modes and therefore does not inform on relative differences between UAM and taxis. Without any data for estimating this with respect to taxis for the NYC case, but given the similarities in role of the air taxi and ground taxi, a conservative assumption is to set a net effect of ASC = 0 because it assumes decisions between air taxi and regular taxi are governed only by quantitative factors like costs and distances. Having a non-zero ASC would not change the optimal decision variables in the HLP since it's uncapacitated (i.e. the optimal skyport locations would not change); only the objective value would change. This is similar to how all the stochastic route choice models in the literature only look at differences in generalized travel costs without any ASCs for specific routes (see Dial, 1971). In the future when operational data is available, an ASC can be calibrated such that the input data like maximum demand for air taxis are better fit. Therefore, eqs. (4) and (5) can be expressed as:

$$U_{n,groundtaxi} = 0.0313 \times c_{ij} - 0.0125 \times f_{ij} + \epsilon_{groundtaxi} \tag{6}$$

$$U_{n,airtaxi} = 0.018 \times d_{kj} - 0.0213 \times f_{ikj} + \epsilon_{airtaxi} \tag{7}$$

Applying eq. (3), the variable f_{ikj} in eq. (7) can be expressed as the total cost of the multi modal trip (i.e, origin to skyport via ground taxi and skyport to destination via air taxi, as shown in Fig. 1) including transfer cost, as shown in eq. (8).

$$U_{n,airtaxi} = 0.018 \times d_{kj} - 0.0213 \times (f_{ik} + t_k + f_{kj}) + \epsilon_{airtaxi} \tag{8}$$

Note that the trip length values via air taxi are smaller than the trip costs so the utility is generally negative overall, and the positive trip length (i.e., travel time and travel distance) coefficients reflect user preferences such that people farther away in distance prefer using air taxi and longer in time prefer ground taxi. Furthermore, both the cost variables f_{ij} and f_{ikj} are functions of corresponding ground trip times and trip distances (refer calculation details in Section 3.2.3). Therefore, in a scenario where, for a given distance the ground trip time increases due to congestion, there is a proportional increase in its trip cost which eventually affects the user choice behavior. Essentially, the air taxi demand to the skyports is based on trade-offs between trip length and trip cost based on user preferences.

Based on the mathematical structure of the binary logit model (McFadden et al., 1973), eqs. (9) and (10) denote the choice probabilities of air taxi and ground taxi.

$$P_{airtaxi} = \frac{e^{V_{airtaxi}}}{e^{V_{airtaxi}} + e^{V_{groundtaxi}}} \tag{9}$$

$$P_{groundtaxi} = 1 - P_{airtaxi} \tag{10}$$

The choice behavior of the origin population in Eq. (9) can be used to estimate the aggregate air taxi demand flow originating from i to destination j that is routed via a skyport at location k. Therefore, we define population choice behavior θ_{ikj} (based on $P_{airtaxi}$) as:

- $\theta_{ikj} \triangleq$ population choice probability of using air taxi service from origin i to destination airport j if routed via skyport k with $i \in \mathscr{L}$, $k \in \mathscr{L}, j \in \mathscr{J}, 0 \leq \theta_{ikj} \leq 1$.

Using eqs. (6) and (8) in eq. (9), θ_{ikj} can be expressed as eq. (11):

$$\theta_{ikj} = \frac{e^{0.018\times d_{kj} - 0.0213\times(f_{ik}+t_k+f_{kj})}}{e^{0.018\times d_{kj} - 0.0213\times(f_{ik}+t_k+f_{kj})} + e^{0.0313\times c_{ij} - 0.0125\times f_{ij}}} \tag{11}$$

Eq. (11) can be used to estimate the probability of a regular taxi user switching to air taxi service for given attribute values.

Note that only one skyport is assigned to each location; under this assumption, the demand function Eq. (11) need not be used as a constraint within the optimization model. Instead, we exploit the structure of the problem to pre-compute all the probabilities of Eq. (11) to use as objective coefficients (*e.g.,* with 150 (taxi) zones, 3 airports, and 150 candidate skyport locations in NYC, there are 67,500 values) for an integer linear programming model.

3.2.6. Optimization problem

Using Equations (1), (2) and (11), we develop an optimization model under two different objectives. Due to the enumeration of the mode choice into an objective coefficient, we can formulate the skyport location problem as an integer linear program.

- **RDR model** (maximize ridership): Equations (12)-(16) optimizes the skyport locations such that the total air taxi ridership (*i.e.,* total airport trips going via skyports) is maximized.

$$\max \sum_{i\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{L}} \theta_{ikj} D_{ij} x_{ikj} \tag{12}$$

$$s.t. \quad \sum_k x_{ikj} = 1 \quad \forall i \in \mathscr{L}, j \in \mathscr{J} \tag{13}$$

$$x_{ikj} \leq y_k \quad \forall i, k \in \mathscr{L}, j \in \mathscr{J} \tag{14}$$

$$\sum_k y_k = p \tag{15}$$

$$x_{ikj}, y_k \in \{0, 1\} \quad i, k \in \mathscr{L}, j \in \mathscr{J} \tag{16}$$

- **REV model** (maximize revenue): Equations (17)-(21) optimizes the skyport locations such that the total air taxi revenue (*i.e.,* total air taxi fare collected from the airport trips made via skyports) is maximized.

$$\max \sum_{i\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{L}} (f_{ik} + f_{kj}) \theta_{ikj} D_{ij} x_{ikj} \tag{17}$$

$$s.t. \quad \sum_k x_{ikj} = 1 \quad \forall i \in \mathscr{L}, j \in \mathscr{J} \tag{18}$$

$$x_{ikj} \leq y_k \quad \forall i, k \in \mathscr{L}, j \in \mathscr{J} \tag{19}$$

$$\sum_k y_k = p \tag{20}$$

$$x_{ikj}, y_k \in \{0, 1\} \quad i, k \in \mathscr{L}, j \in \mathscr{J} \tag{21}$$

where θ_{ikj} (in Equations (12) and (17)) refers to the expression in Equation (11), which is pre-processed to use as input to the models.

The objective function (12) maximizes the airtaxi ridership for each origin-destination pair, while the objective function (17) maximizes the revenue generated by air taxi ridership for each origin-destination pair. Constraints (13) and (18) allow single allocation (*i.e.*, each origin node that passes through a skyport is allocated to only one skyport), while constraints (14) and (19) ensure that demand for each destination j at an origin node i is satisfied via the node at k if and only if a skyport is located at k. Constraints (15) and (20) denote that the total number of skyports to be located is p. This is an indirect measure of the fixed cost; alternatively, if unit fixed costs are known exactly with respect to the other costs in the objective, they can be added to the objective as a fixed charge term. In our case, the budget constraint approach is used in combination with sensitivity analysis of the budget (see Tables 3–5) to give a decision-maker the flexibility to compare costs once they know the fixed costs. For revenue calculation, we consider the air taxi operation model proposed by Holden and Goel (2016) where the end-to-end air taxi trip (*i.e.,* ground transportation access to skyports and air taxi ride to airports) is provided by a single operator. Other air taxi service operators planning to provide service only from skyports to multiple destinations may have different pricing strategies. For example, the helicopter service by Uber in NYC (UberCopter, 2019) comprises of access and egress ground trips along with aerial ride to the airport, and charges passengers for the end-to-end journey (average cost ranges between \$200 - \$225). On the other hand, the BLADE helicopter service that transports passengers only from helipads to NYC airports costs between \$145 to \$195 (Ott, 2019). The air taxi price values in our study is based on estimates by Uber (Dickey, 2018), hence the revenue in our setup includes total revenue generated from end-to-end multimodal air taxi trips.We provide additional analysis in Section 4.2 which is a special case of the REV model; here the revenue calculation is based only on the air taxi rides from skyports to airports.

We solve the model in Section 3.2.6 using the Gurobi optimization tool (Gurobi Optimizer 9.0). For integer programming problems, Gurobi uses multiple solution methods to obtain an exact solution, *e.g.,* parallel branch-and-cut algorithms, non-traditional tree-of-trees search algorithms, cutting plane methods, and symmetry detection.

3.3. Illustrative example

To illustrate the properties of RDR and REV models, the following example is used. Consider 7 origin locations (in set $\mathscr{O}$: \{1,2,3,4,5,6,7\}) and 2 destination facilities (in set $\mathscr{D}$: \{A,B\}) distributed in a Euclidean space. Each origin has direct connection to each destination ((*e.g.,* ground taxi connections); the aggregate demand from origin to destination via direct connections are shown in Fig. 3. The objective is to select 2 skyports (among 7 candidate skyport locations in $\mathscr{S}$: \{1,2,3,4,5,6,7\}) to connect each origin to destination facilities via these skyports. Table 1 shows probability of users (in $\mathscr{O}$) choosing to go via a skyport (in $\mathscr{S}$) to reach a destination (in $\mathscr{D}$), while Table 2 shows the total fare associated with such trips. The value corresponding to row i (*e.g.,* $O1$) and column $k-j$ (*e.g.,* $S1-B$) in Table 1 represents the choice probability of users in origin i to go via a skyport at k to reach destination j (*e.g.,* $O1 - S1 - B = 0.66$); Table 2 follows a similar notation. The values displayed in Tables 1 and 2 are only for illustration purpose in this example.

Using the values of demand, choice probabilities, and fare in this example, we define the parameters used in the optimization models (Section 3.2.6) to determine optimal skyport locations. In this case, $p =$

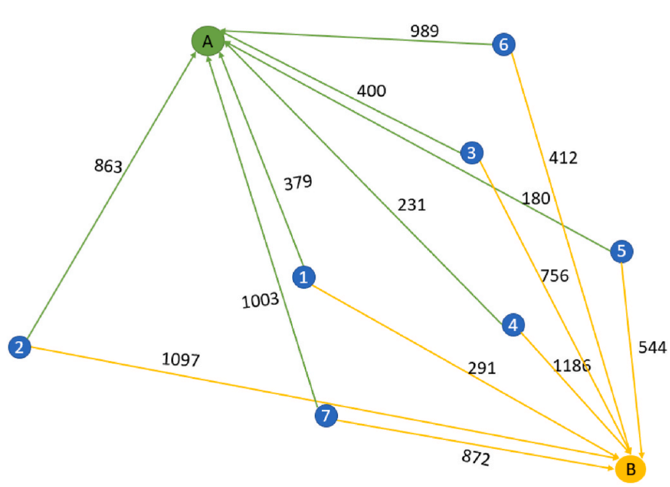


Fig. 3. Illustrative example showing 7 origin locations and 2 destinations; each link displays aggregate demand going from origin to destination via direct connection.

2; Tables 1 and 2 provide θ_{ikj} and $f_{ik} + f_{kj}$ values respectively (where i denotes origin, k is skyport and j denotes destination). The values of parameter D_{ij} are as per the numbers shown in Fig. 3 for origin i to destination j. Therefore, for a candidate skyport in set $\mathscr{S}$, for example at location 3($S3$), the demand from origin at 2($O2$) to destination A via skyport $S3$ is calculated by multiplying the user probability $O2 - S3 - A$ from Table 1 by the aggregate demand from location 2 to A in Fig. 3. Therefore, 363 riders (0.42×863) from $O2$ would choose to go via skyport $S3$ to destination A; the revenue generated from these air taxi riders is obtained by multiplying the ridership with corresponding air taxi fare for $O2 - S3 - A$ in Table 2 which gives \$40, 656 (363×112). Also for $O2$, this means 500 out of 863 users directly go to A without using skyports.

Similarly, the air taxi demand from different origins to each candidate skyport (going to destinations A and B) are computed to be used in the location-allocation decision process for obtaining an optimized set of skyport locations based on the objective in Section 3.2.6. Substituting the parameter values considered in this illustrative example in the RDR model (eqs. (12)-(16)), the optimal choice of skyports are at location 1 and 4, whereas the REV model (eqs. (17)-(21)) result in optimal skyport locations at 5 and 7. The skyport locations and allocation of origin demand to the selected skyports for each destination (obtained using Gurobi) are shown in Fig. 4. Therefore, the total air taxi ridership (demand) at selected skyports (shown in Fig. 4) obtained by RDR model is 5363 compared to 4802 by REV model. The total estimated revenue from potential air taxi riders in this example are \$677,831 and \$742,621 as obtained from RDR and REV models respectively.

4. Data set and experimental results

We first describe the NYC data sets and tools used for our experiments, and then go over the results of our approach.

4.1. Data set and tools

4.1.1. Data set

The study area includes five boroughs in NYC (The Bronx, Manhattan, Queens, Brooklyn and Staten Island) that are divided into 263 taxi zones (New York City taxi zones); each taxi zone has a unique zone ID. The centroids of the taxi zones are the trip origin nodes (locations) while the trip destinations are the three major airports in NYC, *i.e.,* EWR (Newark), JFK and LGA (LaGuardia). The NYC taxi and limousine commission FHV (for-hire-vehicles) trip record data from 2019 (July to December) are used (New York City Taxi Limousine Commission) on our study. This is a publicly available data set, and the motivation for using FHV trips data for airport transfer is derived from the study by Ma et al. (2017). Their study indicated that 65% of trips to JFK are via FHV and taxis.

Each trip record includes the origin and destination locations of the trip in terms of taxi zone IDs. For example, taxi zone IDs for Newark, JFK and LaGuardia airports are: 1, 132 and 138 respectively. The data set contains over 20 million trip records and each trip record includes the start time stamp, origin taxi zone ID, end time stamp, and destination taxi zone ID for the trip. All the trips with trip time (*i.e.,* end time stamp - start time stamp) greater than 120 min were disregarded from the dataset along with other outliers. Furthermore, to avoid distortion in average or aggregate values, major holidays such as Independence day, Halloween, Thanksgiving, Christmas were filtered out before performing any calculations.

Assuming the skyport operations are likely to schedule from 7 a.m. to 6 p.m. (Goyal, 2018), we only consider the trips during this period for demand calculation. The total airport demand and travel costs were calculated using a script written in Python programming language (version 3.7.4). For each origin-destination ID pair in the FHV data set, the total trips were added to obtain the total demand from the origin ID to the destination ID. The trips with destinations as airports (*i.e.,* with

Table 1
Air taxi choice probabilities (θ_{ikj}) of users; each cell in the table shows user probability of choosing to go via a skyport $k \in \mathscr{S}$ from an origin location $i \in \mathscr{O}$ to a destination $j \in \mathscr{D}$: for illustrative example.

	S1-A	S2-A	S3-A	S4-A	S5-A	S6-A	S7-A	S1–B	S2–B	S3–B	S4–B	S5–B	S6–B	S7–B
O1	0.66	0.59	0.51	0.39	0.52	0.51	0.32	0.66	0.47	0.44	0.58	0.3	0.56	0.33
O2	0.58	0.66	0.42	0.35	0.41	0.21	0.5	0.63	0.62	0.37	0.4	0.44	0.38	0.46
O3	0.65	0.41	0.67	0.47	0.45	0.51	0.53	0.48	0.55	0.62	0.32	0.34	0.52	0.51
O4	0.6	0.53	0.53	0.68	0.31	0.4	0.39	0.39	0.37	0.54	0.68	0.54	0.44	0.35
O5	0.42	0.31	0.43	0.52	0.64	0.56	0.46	0.47	0.61	0.45	0.58	0.61	0.32	0.4
O6	0.5	0.57	0.37	0.45	0.55	0.65	0.31	0.39	0.57	0.45	0.65	0.58	0.69	0.43
O7	0.49	0.36	0.41	0.4	0.35	0.39	0.59	0.55	0.54	0.4	0.46	0.34	0.42	0.52

Table 2
Total fare (USD) associated with air taxi trip (f_{ikj}) from an origin $i \in \mathscr{O}$ to a destination $j \in \mathscr{D}$ via a skyport $k \in \mathscr{S}$ including access cost from origin to skyport (f_{ik}) and air taxi cost from skyport to destination (f_{kj}): for illustrative example.

	S1-A	S2-A	S3-A	S4-A	S5-A	S6-A	S7-A	S1–B	S2–B	S3–B	S4–B	S5–B	S6–B	S7–B
O1	180	178	181	185	189	126	104	111	122	156	162	141	155	191
O2	115	118	112	184	114	100	166	119	115	186	138	142	100	174
O3	124	173	149	195	193	134	117	155	129	164	103	124	131	171
O4	149	166	195	101	145	191	135	133	179	173	111	196	175	105
O5	114	145	190	184	101	160	183	105	168	121	160	155	198	187
O6	103	193	200	180	194	162	125	192	172	117	157	178	182	189
O7	123	140	132	120	130	170	151	118	104	169	157	173	124	142

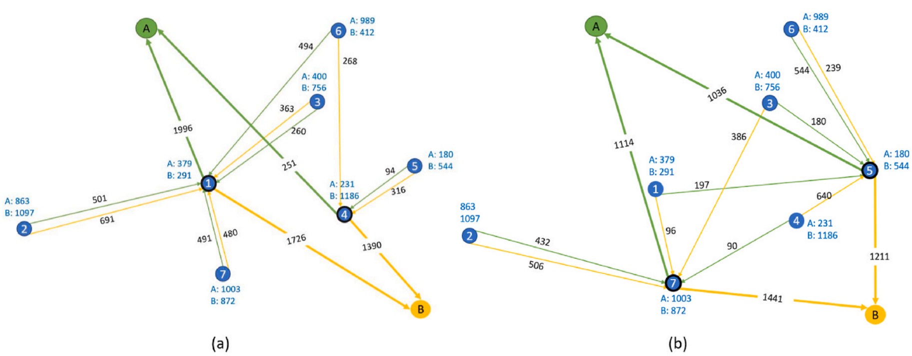


Fig. 4. Comparison of location-allocation solutions of RDR model in (a) and REV model (b). The figure shows allocation of air taxi demand from each origin to the selected skyport locations (highlighted in black outlines); links are color coded as per destination choices. Values on links connecting origin i to skyport k denote air taxi riders originating from i going via skyport k to their respective destinations, while those connecting skyport k to destination j is the aggregate air taxi demand allocated to k to be transport to j. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

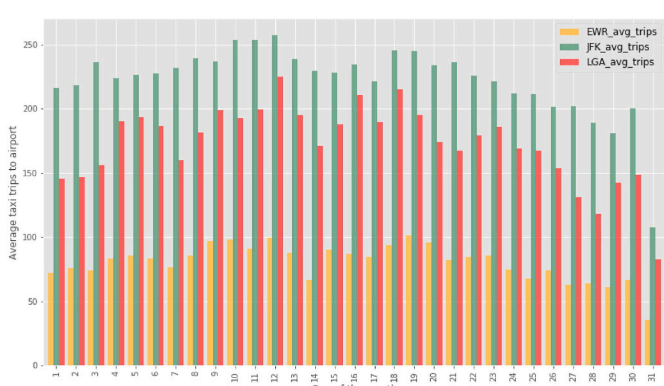


Fig. 5. Daily (average) taxi demand to three major airports in NYC (originating from all taxi zones).

destination taxi zone IDs 1, 132 and 138) were selected and used to compute the demand D_{ij} from origin i to destination airport j. We found the average monthly trips originating from each of the taxi zones to the three airports; we refer to this as D_{ij}. Fig. 5 shows the profile of daily (average) taxi trips to the three airports in NYC.

4.1.2. Data pruning

To further prune the data set, we filter out taxi zones which do not have significant demand to airports. The filtering process was implemented using the demand data D_{ij} (as obtained in Section 4.1.1). For our experiments, we excluded the taxi zones with the lowest fraction of trips (*i.e.,* zones with less than 10 airport trips in a month) and as a result focused on the remaining 149 taxi zones (*i.e.,* the top 149 zones contributing to the airport demand). Fig. 6 shows a choropleth map of the candidate taxi zones generated using ArcMap version 10.5.1 (ArcGIS desktop). Hence, as per the notation defined in Section 3.2.1, $|\mathscr{L}| = 149$ and $|\mathscr{J}| = 3$ (*i.e.,* three airports).

4.1.3. Calculation of travel costs

The input to the skyport location problem is composed of total trips to each airport from each taxi zone (D_{ij}) and the associated trip travel costs across taxi zones (including airports). The travel costs include trip time, trip distance and trip cost (*i.e.,* trip fare). For extreme case scenario, we consider weekday rush hours in NYC (*i.e.,* 4–7 p.m.)[2] to reflect on congested conditions for calculating the parameters defined in Section 3.2.3.

The average peak hour ground travel time (c_{ik}, c_{kj}) and average ground trip distance (d_{ik}, d'_{kj}, d_{ij}) across taxi zones and airports were found using Google Maps Distance Matrix API and Python programming language; values were obtained during 5pm–6pm (peak hours) on a weekday. The aerial distance (d_{kj}) was calculated based on the relation

[2] www1.nyc.gov/site/tlc/passengers/taxi-fare.page#.

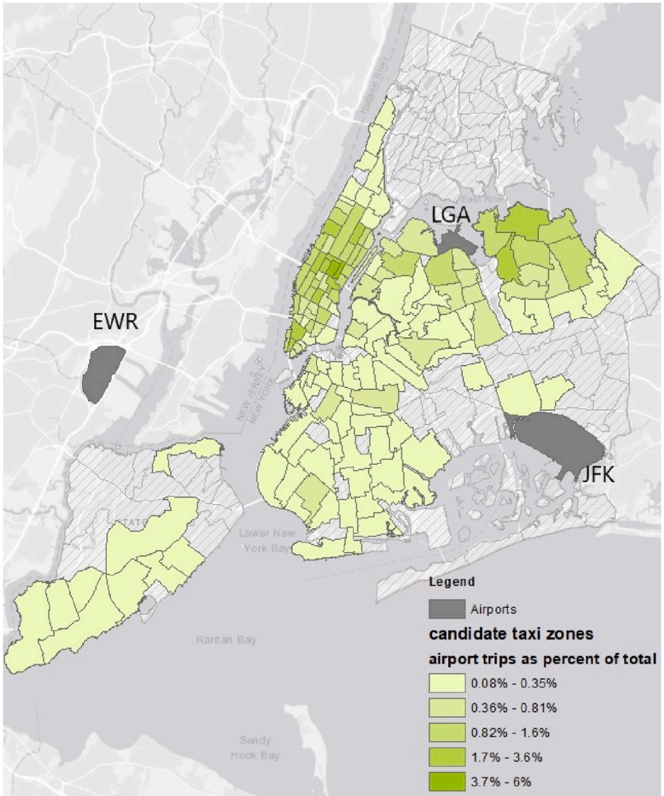


Fig. 6. Choropleth map showing the candidate taxi zones with taxi zone-wise demand for the three airports in NYC with zone shading.

between ground miles and aerial miles (Goyal (2018)):

$$\begin{aligned} Groundmiles &= 1.42 \times Airmiles \\ \Longrightarrow d'_{kj} &= 1.42 \times d_{kj} \\ \Longrightarrow d_{kj} &= \frac{d'_{kj}}{1.42} \end{aligned} \tag{22}$$

For trip fare calculations, we consider the ground transportation fare structure (used by taxi services in NYC) associated with trip time and trip distance values; the cost components include a Booking fee (*Basefee*), a per mile cost (R_{mile}), and a per minute cost (R_{minute}). Therefore, the ground taxi (access) fare from origin to candidate skyport (f_{ik}) and direct ground taxi fare from origin to airport (f_{ij}) can be written as:

$$f_{ik} = Basefee + R_{mile} \times d_{ik} + R_{minute} \times c_{ik} \tag{23}$$

$$f_{ij} = Basefee + R_{mile} \times d_{ij} + R_{minute} \times c_{ij} \tag{24}$$

Based on average market rates in NYC (Majaski (2019)), we consider the following values for f_{ik} and f_{ij}:

- $Basefee = \$3$
- $R_{mile} = \$1.5$
- $R_{minute} = \$0.3$
- Minimum ground taxi fare between taxi zones: $7
- Minimum fare for ground taxi trip with pick up or drop off location in Manhattan: $8 and an additional congestion charge of $2.75 (Hu, 2019)

Using the above values in Equations (23) and (24), the access taxi fares to skyports and direct ground taxi fares to airports were computed for different values of trip times and trip distances (for each origin zone).

The flight leg fare of an air taxi trip *i.e.,* f_{kj} was determined by multiplying the aerial distance d_{kj} (Eq. (22)) by the price per air mile. It is possible that for passengers sharing the same destination, an air taxi serves more than one passenger at a time, but for worst case analysis, we consider average passenger occupancy as 1. Therefore, assuming one air mile is equivalent to one passenger mile, let the price per air mile be represented as $R_{airmile}$ such that:

$$f_{kj} = R_{airmile} \times d_{kj} \tag{25}$$

Based on ST, MT and LT scenarios (as explained in Section 3.2.1), the values of $R_{airmile}$ include:

- $R_{airmile} = \$5.73$ for short term
- $R_{airmile} = \$1.86$ for medium term
- $R_{airmile} = \$0.44$ for long term

Using Equations (23) and (25), the total air taxi fare f_{ikj} in Eq. (3) consisting of access fare, transfer cost, and flight leg fare can be written as:

$$\begin{aligned} f_{ikj} &= f_{ik} + t_k + f_{kj} \\ \Longrightarrow f_{ikj} &= Basefee + R_{mile} \times d_{ik} + R_{minute} \times c_{ik} + t_k + R_{airmile} \times d_{kj} \\ \Longrightarrow f_{ikj} &= Basefee + R_{mile} \times d_{ik} + R_{minute} \times c_{ik} + R_{minute} \times (\alpha_1 + \alpha_2) + R_{airmile} \times d_{kj} \\ \Longrightarrow f_{ikj} &= Basefee + R_{mile} \times d_{ik} + R_{minute} \times c_{ik} + R_{minute} \times (tt) + R_{airmile} \times d_{kj} \\ \Longrightarrow f_{ikj} &= Basefee + R_{mile} \times d_{ik} + R_{minute} \times (c_{ik} + tt) + R_{airmile} \times d_{kj} \end{aligned} \tag{26}$$

where $tt = \alpha_1 + \alpha_2$ is the equivalent in-vehicle time for transfers to and from skyports.

For the total transfer time (tt), we base our assumption of α_1 on previous findings. For example, the transfer time for rail transit was found to be valued at approximately 8 min of in-vehicle time (Wardman et al., 2001). For the transfer time α_2 *i.e.,* the last mile transfer between a landing zone (located nearest to a destination airport) and the destination airport terminal, we consider existing helicopter services in NYC (Blade; UberCopter, 2019) that use helipads near airports for landing and transferring passengers from helipads to the airport terminals via ground taxi or shuttle (Taylor, 2019). For example, the average ground taxi time from heliport at JFK airport to the JFK terminal is between 5 and 8 min.[3] Therefore, we assign tt as 15 min (*i.e.,* $\alpha_1 = 8$ min and $\alpha_2 = 7$ min). Using the values of tt and $R_{airmile}$ in Equation (26) we computed air taxi fares from each origin i to each candidate skyport location k ($i, k \in \mathscr{L}$) to each destination airport j ($j \in \mathscr{J}$) for different scenarios *i.e.,* ST, MT, LT (to be used for demand estimation and revenue calculation in the optimization models explained in following Section 4.2).

4.1.4. Tools

To solve the proposed optimization problems (as described in Section 3.2.6), Gurobi optimization tool (Gurobi Optimizer 9.0) and Python programming language (version 3.7.4) were used. Based on 149 taxi zones and 3 airports, the optimization problem for NYC consisted of 66, 752 binary variables and zero continuous variables. Our experiments were carried out on a computer with Intel i7 processor with 2 cores, 4 logical processors and 16 GB RAM with an average computation time below 10 s (for solving an instance of the optimization problem in Gurobi for the above data set).

4.2. Optimization results

Using the data obtained for the 149 taxi zones to the 3 airports (as explained above), we pre-computed all possible values of population air taxi choice probabilities (θ_{ikj}) in Equation (11) for each origin zone to each candidate skyport (going to multiple airports). Using the obtained values, we solved the proposed optimization models *i.e.,* RDR and REV

[3] www.google.com/maps/dir/Heliport+at+JFK+Airport,+Queens,+NY/JFK + Airport,+Queens,+NY.

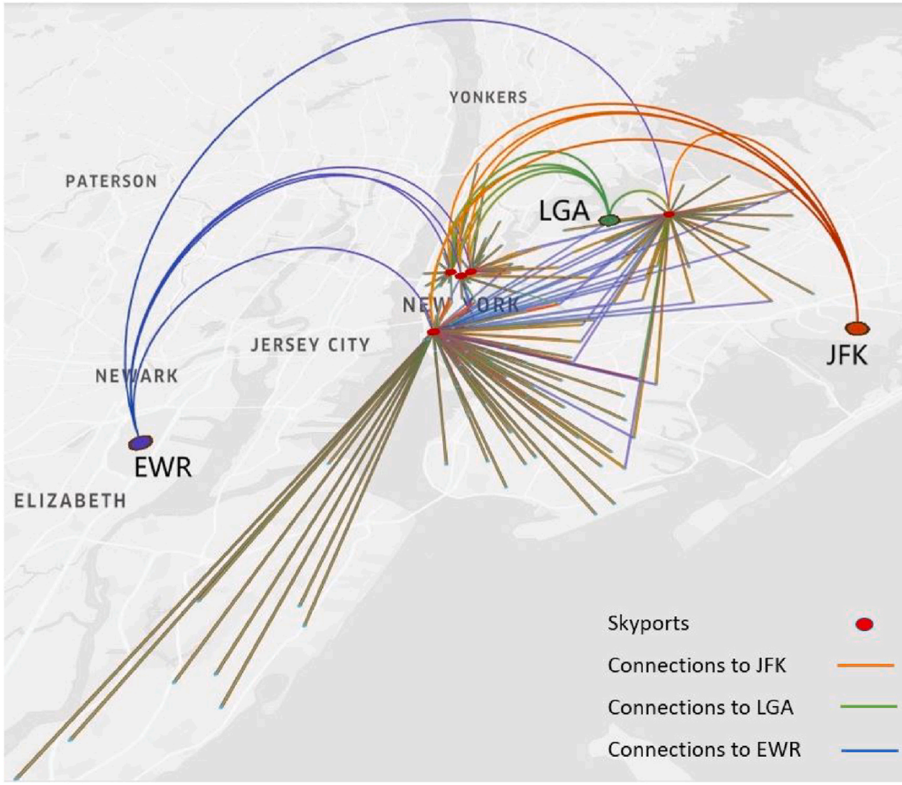


Fig. 7. Demand allocation showing connecting edges between origin taxi zones to three airports in NYC via $p = 5$ skyports (output of RDR model for long term scenario). The edges connecting trip origin locations to skyports are color coded as per destinations. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Optimization results for short term scenario.

Budget	RDR model			REV model		
number of skyports	Airtaxi market share	Flight leg revenue share	Increment in total revenue	Airtaxi market share	Flight leg revenue share	Increment in total revenue
(p)	(%)	(%)	(%)	(%)	(%)	(%)
1	13.21	60.14	–	11.87	72.31	–
2	14.95	38.15	−5.12	12.82	63.71	3.70
3	16.22	39.14	−1.79	13.48	69.77	4.97
4	16.73	44.98	−2.49	13.57	72.22	5.80
5	16.92	49.31	−1.13	13.64	76.42	6.58
6	17.07	48.28	−1.64	13.92	78.25	7.29
7	17.21	52.01	−0.38	14.16	78.66	7.97
8	17.32	52.39	0.05	14.29	79.38	8.53
9	17.42	54.92	0.92	14.30	79.73	8.98
10	17.52	56.32	1.34	14.34	80.19	9.38

(described in Section 3.2.6). The objective value of RDR model provides average monthly air taxi ridership, while the REV model objective value gives the average monthly air taxi revenue. We used these models to find optimal skyport locations for three price scenarios (refer Sections 3.2.1 and 4.1.3). For each case, we obtained results (using our Gurobi implementation) for different values of $p \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$ (where p is the number of skyports). Fig. 7 demonstrates the demand allocation from different origin to multiple airports via optimal skyports in NYC (obtained for the case of p = 5 in RDR model for LT scenario).[4] The edges connecting origin to skyport (for multiple airports) as shown in the figure are the outcome of the optimization models (*i.e.*, x_{ikj}).

Using the optimal skyport locations, it is possible to estimate the ridership for the REV model and revenue for RDR model respectively. The air taxi ridership corresponds to the total trips to airports originating from different origin taxi zones that are routed via optimal skyports from REV model (k^*_{REV}). This is calculated by multiplying population choice probability θ_{ikj} (from the demand model) with airport trips D_{ij} where $k = k^*_{REV}$. Similarly, the air taxi revenue for the optimal skyports from RDR model (k^*_{REV}) is computed by multiplying air taxi ridership with the revenue generated from the multimodal trips ($f_{ik} + f_{kj}$) for $k = k^*_{REV}$. Tables 3–5 summarize optimization results obtained from RDR and REV models for short term, medium term and long term price scenarios; details of optimal skyport locations are reported in Section 5. The ridership and revenue values in the results are average monthly estimates. For each choice of skyport budget p, the data in Tables 3–5

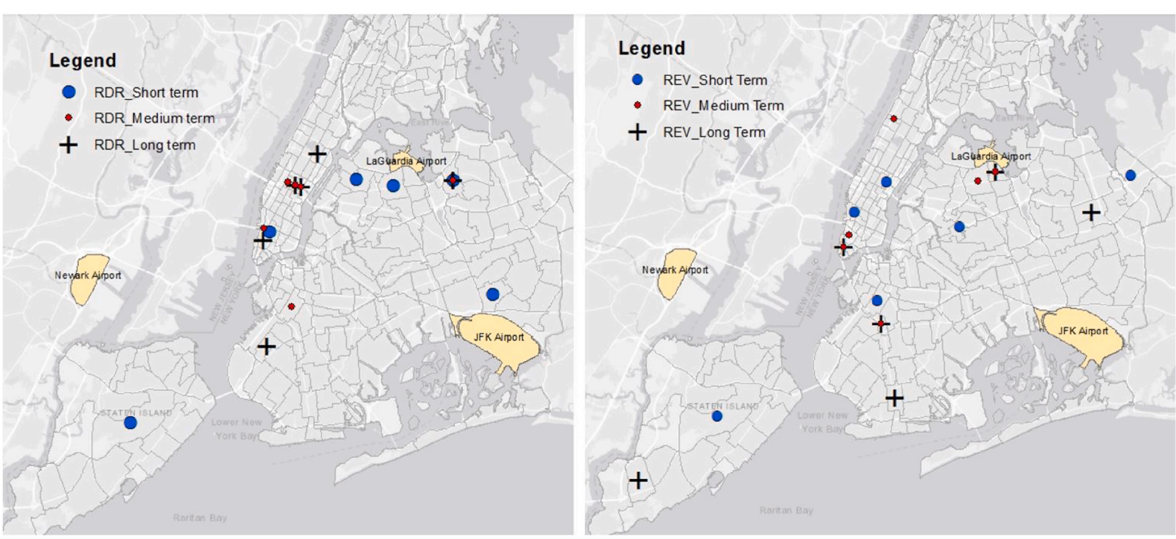
[4] Visualization was done using the kepler.gl tool.

Table 4
Optimization results for medium term scenario.

Budget	RDR model			REV model		
number of skyports	Airtaxi market share	Flight leg revenue share	Increment in total revenue	Airtaxi market share	Flight leg revenue share	Increment in total revenue
(p)	(%)	(%)	(%)	(%)	(%)	(%)
1	22.22	47.10	–	15.39	43.91	–
2	24.19	50.75	−7.65	15.29	56.88	7.53
3	25.04	54.10	−9.46	16.27	58.34	8.15
4	25.62	56.45	−10.78	16.35	58.58	8.36
5	26.02	58.23	−11.50	16.11	58.46	8.55
6	26.38	59.45	−12.24	16.21	58.78	8.66
7	26.68	60.91	−13.02	16.33	58.78	8.76
8	26.98	61.73	−14.00	16.31	58.78	8.80
9	27.25	62.97	−14.17	16.40	58.96	8.83
10	27.50	64.11	−15.16	16.41	59.00	8.86

Table 5
Optimization results for long term scenario.

Budget	RDR model			REV model		
number of skyports	Airtaxi market share	Flight leg revenue share	Increment in total revenue	Airtaxi market share	Flight leg revenue share	Increment in total revenue
(p)	(%)	(%)	(%)	(%)	(%)	(%)
1	27.55	17.57	–	12.77	11.90	–
2	29.37	20.13	−12.65	14.18	14.40	4.94
3	30.67	24.34	−16.18	15.99	14.99	7.11
4	31.33	26.09	−19.77	18.29	16.96	7.69
5	31.80	27.46	−22.32	18.54	17.05	8.16
6	32.22	29.03	−24.28	18.56	16.91	8.31
7	32.59	30.15	−25.70	18.35	16.62	8.41
8	32.90	31.11	−27.56	18.29	16.61	8.47
9	33.21	32.36	−29.11	18.35	16.60	8.50
10	33.50	33.36	−30.88	18.37	16.64	8.52



(a) (b)

Fig. 8. Optimal skyport locations in NYC (for p = 6) for short term, medium, and long term scenarios. (a) RDR model output (b) REV model output.

include the following:

- Air taxi market share: this denotes the proportion of regular taxi users that are estimated to switch to air taxi service for airport access
- Flight leg revenue share: the total revenue generated from end-to-end air taxi trips in our study includes revenue from ground transportation access to skyports plus revenue from air taxi rides (this constitutes the flight leg of the multi-modal trip). Hence, the flight leg revenue share refers to the percentage revenue generated only from the flight leg (f_{kj}) with respect to the total revenue ($f_{ik} + f_{kj}$)
- Increment in total revenue: this represents percentage increment in total revenue with increasing skyport budget p (increment is measured with respect to baseline $p = 1$)

The output from our experiments clearly depict the sensitivity of skyport locations to different objectives as well as varying price scenarios. To get a sense of the placement of skyports, a visualization in Fig. 8 shows optimal skyport locations (for $p = 5$) in NYC obtained from RDR and REV models for ST, MT, and LT scenarios. While it can be seen that the location choice is sensitive to the objective values considered in the models, there are common zones that are optimal across different scenarios which can guide investment decisions for setting up skyports. For example, for $p = 6$ (as shown in 8), the common skyport zones in NYC include midtown Manhattan and Flushing (Queens) from RDR model, and Park slope (Brooklyn) and Elmhurst (Queens) from REV model. Lower Manhattan area seems optimal for both RDR and REV model.

Moreover, going from short term to long term, it can be seen that with each additional skyport in the budget, the air taxi market share in both RDR model and REV model monotonically increases, although the proportion of market share obtained from RDR model skyports is higher compared to REV model skyports. This is because the objective of RDR model is to maximize the air taxi ridership, thereby resulting in higher values of air taxi market share. Similarly, based on the objective, the total estimated revenue generated from REV model skyports are relatively higher. However, the REV model results in an increment in total revenue from additional skyports, while an opposite trend is observed in the RDR model output (especially for MT and LT scenarios, and at lower values of p for the ST scenario). In this context, REV model shows relatively better performance; there is an increment in both revenue and air taxi market share with increasing skyport budget p (which is desired). Furthermore, for the ST scenario, the REV model output shows a major portion of the total revenue being generated from the flight leg of air taxi trips; the value decreases for MT and LT scenarios due to the lower air taxi prices considered in these scenarios. However, given the higher air taxi market share estimated during the long term, various revenue management strategies can be used to ensure higher revenue from these services (Bitran and Caldentey, 2003; Chiang et al., 2007). As mentioned earlier, we assume a single air taxi operator to provide ground taxi access to skyports with air taxi rides from skyports to airports. For cases where an air taxi operator plans to provide only air taxi rides from skyports to multiple destinations, the revenue calculation used in the REV model objective can be modified accordingly. We discuss this special case of REV model below:

4.2.1. Special case (REV model)

The air taxi revenue considered in the REV model objective (Eq. (17)) includes $f_{ik} + f_{kj}$ *i.e.,* total estimated revenue from end-to-end multi-modal air taxi trips. Let this objective be denoted as obj_{org}. For the special case, we assume the operator is interested in maximizing only the flight leg revenue (based on the type of air taxi service it plans to provide). Hence, the revenue ($f_{ik} + f_{kj}$) in Eq. (17) can be replaced by f_{kj} (keeping constraints in Equations (18)-(21) the same). We refer to this modified objective as obj_{mod}. For comparison purpose (for ST scenario) we assume the same pricing strategy considered for the multi-modal air taxi setup in our study. The choice of optimal skyport locations obtained from solving the REV model with obj_{mod} is different from those obtained using obj_{org}. However, a higher number of common skyport locations were found in both objectives for higher values of p. The REV model with obj_{mod} resulted in 7% lower air taxi ridership for (averaged across different choices of $p \in \{1, 2, 3, \ldots, 10\}$). The flight leg revenue generated using obj_{mod} is comparatively higher (10% on an average) for $p \leq 4$, however, a decreasing trend (with revenue lift of 3–4%) was noticed for higher values of p. Assuming obj_{mod} in the multi-modal air taxi setup (as considered in our study), the total revenue generated from obj_{mod} (by adding ground transportation access revenue with flight leg revenue from obj_{mod}) was found to be 2% less than the total revenue obtained using obj_{org}.

4.3. Demand distribution at skyports

As an outcome of the optimized skyport locations, we estimate the (incoming) demand at each skyport; this demand corresponds to the trips to airports that are routed via a skyport from origin zones (allocated to that skyport). In this subsection, we study the characteristics of such demand vis-a-vis the number of skyports. In particular, given a budget (p) and the optimal skyport locations (k) obtained from RDR and REV models for ST and LT respectively, we compute the total number of (allocated) incoming trips to each skyport. The demand distribution at different skyports is computed using the connections between origin zones and skyports (for each airport) obtained as an outcome of the optimization models (see Section 4.2). These values are then used to calculate the percentage (proportion) demand allocated to each optimal skyport location (with respect to total estimated air taxi demand flow via set of optimal skyports). For the case of $p = \{3, 4, 5, 6, 7, 8\}$, Fig. 9 shows the percentage of airport demand allocated to each skyport. In the short term, an increase in the skyport budget (p) will result in some of the skyports in the RDR model having much lower incoming demand relative to other locations. For example, for $p = 8$, the proportion of incoming trips at one of the skyports is only 1%. For the same scenario (*i. e.,* ST), the REV model skyport locations show relatively fair distribution of air taxi demand. In the long term, however, the proportion of air taxi demand across different skyports is noticed to be fairly distributed in case of both RDR and REV model.

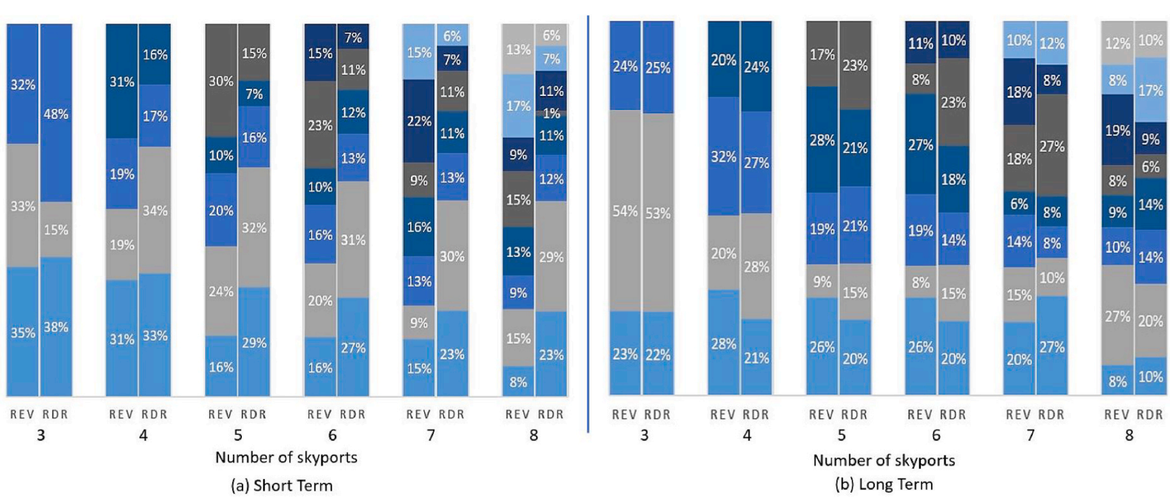


Fig. 9. Airport demand distribution at optimal skyport locations in NYC. Each set of bars represents percentage of demand allocated to each skyport location (given budget of p skyports) obtained from REV and RDR models.

Overall, comparing the outcomes from RDR model and REV model, the performance of the REV model is observed to be relatively better in terms of fair demand distribution at skyports and higher revenue generation (see Section 4.2). The distribution of air taxi demand to different skyport locations based on the choice of the optimization model (and its output) can guide service providers to plan multiple skyport design options. For instance, based on demand at optimal locations, companies can opt for smaller skyports (*e.g.*, accommodating one to three air taxis) at locations with limited demand or they can choose to build skyports with higher capacity and additional facilities at locations with significant incoming demand.

4.4. Sensitivity analysis (time savings)

We investigate the effects of varying total transfer time *tt* to analyze minimum skyport requirements that can accommodate such variations. As the time spent in transfers is a critical part in the end-to-end trip of the air taxi service, we base the decision criterion of our analysis on time savings (*i.e.,* time saved by travelers commuting via air taxi compared to ground taxi while going to the same destination). As discussed earlier in Section 3.2.4, we consider a transfer cost t_k associated with transfer time *tt*; this has a direct impact on user choice behavior and may affect the location allocation of skyports. The transfer time mainly depends on the infrastructure design as well as on the integration of multi modal operations by the service provider; depending on these factors the time spent in transfers can vary. Therefore, it is important to understand the minimum skyport requirements to accommodate these variations. Our analysis is limited to near term only, mainly because such variations are more likely to occur during the short term or initial period while investigating proper integration of different modes and operations design of such new services. Moreover, determining the minimum requirements in the long term would require considering various other factors beside time savings such as competitive services, user experiences, and market evolution of UAM in a city.

For our analysis, we consider the REV model (because of its superior performance) and assume four possible values of *tt*, *i.e.* 10, 15, 20 and 25 min. A study by Garcia-Martinez et al. (2018) suggests the first transfer in a multimodal trip to be equivalent to 15.2 min of the trip in-vehicle time. Using this finding and the values assumed in Section 4.1.3, we consider different choices of α_1 (in range 8–15 min) and α_2 (in range 5–8 min) to define the transfer time set $TT = \{10, 15, 20, 25\}$ for our sensitivity analysis. For each choice of transfer time in *TT* and skyport budget p (where $p \in \{1, 2, 3 \ldots 14, 15\}$), we compute the travel cost values (refer Section 4.1.3) and solve the REV model to get p optimal skyport locations. This is used to calculate the total time savings of trips allocated to the selected skyports (for each p). Using these values we compute the percentage increment in time savings (ts_{inc}) with each

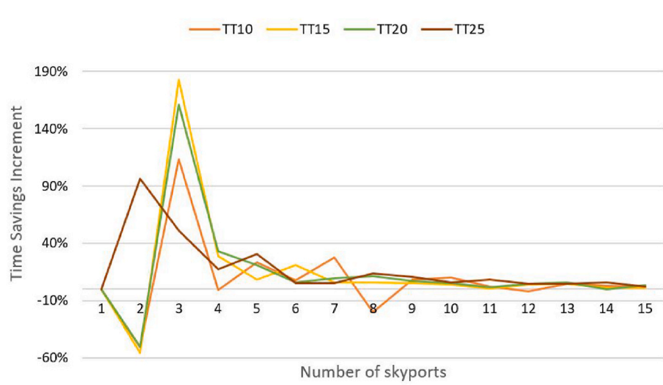


Fig. 10. Comparison of percentage increment in time savings (ts_{inc}) with respect to each additional skyport in budget p (for different choices of transfer time in *TT*).

additional skyport in budget p. Fig. 10 illustrates the variation of ts_{inc} with respect to p for different choices of $tt \in TT$. As shown in the figure, the variation in ts_{inc} (for a given value of p) across different choices of *tt* is significantly higher for lower values of p. Such *sensitivity* to *tt* variations decreases as p increases (with minimum variations observed at $p \geq 9$). Therefore, based on the analysis above, the infrastructure planning for air taxi services (in the near term) requires locating at least 9 skyports across NYC. As per the REV model results (obtained for varying *tt*), the optimal choice includes one skyport each in Union Square, Financial district, Diamond district, Flushing, Murray Hill, Park Slope, Theater District, and 2 skyports near midtown Manhattan.

4.5. Discussion and insights

Our experiments based on the formulated air taxi ridership maximization and revenue maximization optimization models (*i.e.,* RDR and REV models) lead to several valuable insights that may be of interest to air taxi service operators that are planning to start their service in a metropolitan city.

- For a given skyport budget (p), the optimal set of skyports that seem attractive in the short term may not be useful for generating enough revenue in the long run. For a value of p, the common zones that are optimal across different price scenarios can guide infrastructure cost allocation decisions. For example, in NYC (refer Fig. 8), the RDR model results for $p = 6$ (for short term, medium term and long term scenarios) show common skyport zones near lower Manhattan, midtown Manhattan, and Flushing (Queens). It would make sense to allocate more infrastructure budget to design high capacity skyports in these zones.
- It is likely that the service operators, in the near term, would want to gain more riders (to improve familiarity with the technology and increase user adoption). In this context, the initial set of skyports can be planned based on the RDR model. However, the RDR model (for short term scenario) performs well only upto a limited skyport budget (*i.e.,* for $p \leq p_t$). This is because for higher values of p (*i.e., $p > p_t$*), the proportion of trips allocated to some skyports is very less and this may not be able to compensate for high infrastructure costs on such locations. For example, in case of NYC scenario for $p > 7$ (*i.e.,* $p_t = 7$), the percentage of incoming trips at some skyports are very low; for $p = 8$, one skyport has only 1% demand allocated to it ((see Section 4.3)).
- From revenue aspect, the RDR model is not greatly beneficial in the long run compared to REV model. This is because in the long run, the RDR model output does not result in higher revenue with increase in skyport budget (p) although it results in increased ridership (refer Tables 3–5).
- In order for large scale air taxi operations to be sustainable in the long run, the operators would be more interested in planning for maximizing the revenue. In this context, REV model approach can be used determine the skyport choices. The fair demand distribution across different skyports obtained from REV model (see Section 4.3) would ensure promising returns on infrastructure investments at such locations.
- Variation in time savings based on different choices of transfer time could serve as a possible decision criterion (besides budget constraint) for deciding minimum skyport requirements in a city. For example, as per the sensitivity analysis conducted based on time savings (see Section 4.4), it was found that atleast 9 skyports are required in NYC to accommodate variation in transfer times.

The above insights with respect to the incorporation of elastic demand for short term and long term analyses of optimal skyport location choices in a city can facilitate the air taxi infrastructure investment decision and planning process, however, a more in-depth analysis with consideration of various other user factors in the demand model and

Table 6
Optimal skyport locations in NYC for short term scenario.

Budget	RDR model	REV model
number of skyports (p)	skyport locations (taxi zone IDs)	skyport locations (taxi zone IDs)
1	[157]	[170]
2	[10, 260]	[198, 234]
3	[10, 114, 129]	[114, 160, 161]
4	[7, 10, 92, 211]	[114, 161, 162, 198]
5	[7, 10, 92, 161, 211]	[92, 161, 162, 181, 249]
6	[7, 10, 92, 114, 129, 161]	[92, 161, 162, 181, 230, 231]
7	[7, 10, 92, 114, 129, 161, 162]	[92, 161, 162, 170, 181, 230, 231]
8	[7, 10, 92, 114, 118, 129, 161, 162]	[48, 92, 161, 162, 170, 181, 230, 231]
9	[7, 10, 92, 114, 118, 129, 161, 162, 230]	[48, 92, 161, 162, 170, 181, 230, 234, 261]
10	[7, 10, 25, 92, 114, 118, 129, 161, 162, 230]	[48, 92, 161, 162, 170, 181, 230, 234, 239, 261

Table 7
Optimal skyport locations in NYC for medium term scenario.

Budget	RDR model	REV model
number of skyports (p)	skyport locations (taxi zone IDs)	skyport locations (taxi zone IDs)
1	[170]	[257]
2	[92, 161]	[70, 87]
3	[92, 125, 161]	[70, 231, 236]
4	[92, 125, 161, 162]	[70, 231, 236, 257]
5	[92, 125, 161, 162, 230]	[7, 24, 70, 231, 257]
6	[92, 125, 161, 162, 181, 230]	[7, 24, 70, 231, 257, 261]
7	[92, 125, 161, 162, 181, 230, 236]	[7, 24, 70, 231, 243, 257, 261]
8	[92, 125, 161, 162, 170, 181, 230, 236]	[7, 24, 70, 129, 231, 243, 257, 261]
9	[48, 92, 161, 162, 170, 181, 230, 231, 236]	[7, 24, 70, 129, 143, 231, 243, 257, 261]
10	[7, 48, 92, 161, 162, 170, 181, 230, 231, 236]	[7, 24, 70, 118, 129, 143, 231, 243, 257, 261]

Table 8
Optimal skyport locations in NYC for long term scenario.

Budget	RDR model	REV model
number of skyports (p)	skyport locations (taxi zone IDs)	skyport locations (taxi zone IDs)
1	[170]	[204]
2	[92, 161]	[135, 204]
3	[92, 161, 231]	[135, 204, 261]
4	[92, 161, 162, 231]	[70, 135, 204, 261]
5	[92, 161, 162, 230, 231]	[70, 123, 135, 204, 231]
6	[92, 161, 162, 230, 231, 236]	[70, 123, 135, 204, 257, 261]
7	[92, 161, 162, 227, 230, 231, 236]	[70, 98, 123, 135, 204, 257, 261]
8	[48, 92, 161, 162, 227, 230, 231, 236]	[44, 70, 98, 123, 135, 204, 257, 261]
9	[48, 92, 161, 162, 227, 230, 231, 236, 252]	[44, 70, 98, 118, 123, 135, 204, 257, 261]
10	[48, 92, 161, 162, 170, 227, 230, 231, 236, 252]	[44, 70, 98, 118, 123, 135, 204, 231, 257, 261]

operational factors in the optimization models is suggested as future work.

4.5.1. *Effects of varying model parameters*

An important aspect to consider while planning resource allocation to different locations for the skyport network design is the sensitivity of the optimal skyports to varying pricing scenarios. For example, consider the skyport locations obtained using the REV model for $p = 9$ (details in the Appendix Tables 6–8). For the short term and medium term scenarios, if we compare the different pairs of skyports from each scenario (paired simply based on their spatial proximity), it is observed that on an average the shift in skyport choices is within 6 miles distance. Therefore, based on the operational feasibility and the estimated benefits, the optimal skyport locations for short term and medium term can guide planners in designing the skyport network in the common regions (as per spatial proximity) that can sufficiently cater to both short term and medium term needs. However, based on the price transition from medium to long term, it is observed that even though 3 out of 9 skyport choices (obtained using the REV model for the two price scenarios) are common, the average shift is about 15 miles, which is more sensitive compared to the price transition from short term to medium term. Therefore, in the long run, the operator may need to expand the skyport network (either by including additional existing infrastructure or designing new stations based on the budget constraint) to effectively cater to the long term needs. These observations may vary based on the population characteristics and mobility needs in a city. Hence, the above insights with respect to the incorporation of elastic demand for short term and long term analyses of optimal skyport location choices in a city can facilitate the air taxi infrastructure investment decision and evaluation of different pricing schemes in the UAM service deployment planning process. It should be noted that, in the long run, operators may incur additional costs with respect to the increasing fleet size based on the skyport choices and user adoption (Rajendran and Shulman, 2020; Roy et al., 2022), hence the trade-offs between the revenue and cost resulting from increased ridership need to be considered in the planning process. Further information on UAM services from pilot deployments in cities may be needed to better analyze the impacts of different parameters to the operator's profit.

Moreover, it is possible that the user demand, travel time and other factors related to UAM adoption may change over time and in response to the location decisions. With respect to uncertainties, stochastic variant of HLP models have been studied in the literature (Snyder, 2006). However, to properly model the uncertain parameters into the location-allocation decision process would require some knowledge on either the probability distributions or some pre-specified intervals for the uncertain parameters. Due to the emerging technology aspect of UAM services, obtaining such data is difficult since they have not been implemented yet. As more information becomes available on the use and impact of UAM services in different cities, a more in-depth analysis with consideration of various other user factors in the demand model along with incorporation of uncertainty and operational factors in the optimization models is suggested as future work.

5. Conclusion

We formulated the skyport location optimization problem for access to special destinations like airports as a variant of HLP while incorporating elastic demand toward air taxi services. Our linearized formulation can be readily solved using commercial software like Gurobi for scenarios like that of NYC; this can be easily extended to include healthcare facilities, sports venues, and major transportation hubs in addition to airports. We formulated an optimization model with two alternative objectives in our study *i.e.,* RDR model with an objective to maximize air taxi ridership, and REV model with an objective to maximize air taxi revenue. Depending on the objective, the model allocates demand from different origin zones across optimal skyports (for each destination). The demand to the skyports is based on trade-offs between trip length and trip cost based on user preferences. These preferences are incorporated in the skyport location problem using a binary mode choice logit model. We consider different price scenarios (estimated by Uber for air taxi services) in our analysis such as short term, medium term and long term.

The case study of NYC was presented considering airport access/transfers as a use case for air taxis. Using a dataset from NYC TLC with over 20 million FHV trips to major airports associated with NYC (*i.e.*, JFK, EWR, and LGA), we obtained the optimal locations for skyports for air taxis using RDR and REV models for each price scenario. Choosing the right objective and approach to locate skyports has a great impact on potential air taxi ridership as well as on the returns gained from such services.

The choice of skyport location and allocation of demand at each skyports based on user behavior was used to study the demand distribution at each skyports; it was found that the REV model results in fair distribution of demand across skyports compared to RDR model. Also, from revenue aspect, the REV model shows relatively better performance.

Another important insight is around the choice of minimum number of skyports. In this context, we considered variation in travel time savings (increment) across different choices of transfer time as a decision criterion. The number of skyports in a city should be able to handle variations in transfer time; this is reflected via increase in travel time savings with respect to skyport budget (p). The results of sensitivity analysis for NYC (based on optimal skyport locations using REV model) show that at least 9 skyports would ensure good performance in the near term.

Although our study is based on a (major) subset of demand, and selected (significant) decision variables reflecting user preferences, the method used in the analysis of optimal skyport locations considering short term and long term scenarios can help air taxi providers pursue various skyport design options based on infrastructure location choices. In terms of future directions, the research can be further refined and elaborated along the following lines:

- the optimization problem can be augmented by considering different modes of access to skyports (*e.g.*, bike, walk, e-scooters, public transit) and adding other eligible (mostly long commute) trips for potential demand estimation,
- updating demand model with other competitive modes (see Fu et al., 2019; Sun et al., 2018) and with additional influencing factors (*e.g.*, individual specific decision variables capturing changes in perceptions in post-pandemic scenario),
- considering aerial (flight) restrictions, regulations, and noise related factors pertaining to operations in cities as per the city structure,
- considering access to medical facilities and daily long commutes as additional factors driving UAM adoption,
- incorporating queue management using pricing schemes,
- modeling stochasticity in travel time and demand,
- using simulation based modeling approaches (see Rothfeld et al., 2018a) to study overall performance,
- considering capacity effects at skyports (see Vascik and Hansman, 2019); one way would be to assign travelers to skyports with nonbinding capacities, which would also consider potential for transfers between hubs,
- developing robust optimization methods with additional heuristics, and
- queue sensitive air taxi rebalancing (motivated by similar work for ground transportation by Sayarshad and Chow (2017)).

Finally, although our results are focused on NYC, the methods are easily applicable to other cities as well.

Author statement

The authors confirm contribution to the paper as follows: study conceptualization and methodology design: SR, JYJC; data collection: SR; formal analysis and interpretation of results: SR, JYJC; draft manuscript preparation: SR, JYJC.

Tables 6–8 report optimal skyport locations obtained from our experiments (for different pricing scenarios).

Acknowledgement

The authors wish to thank the C2SMART University Transportation Center at NYU for its support for their research project, under U.S. Department of Transportation grant #69A3551747124.

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