Air Taxi Skyport Location Problem for Airport Access

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Abstract

Air taxis are poised to be an additional mode of transportation in major cities suffering from ground transportation congestion. Among several potential applications of air taxis, we focus on their use within a city to transport passengers to nearby airports. Specifically, we consider the problem of determining optimal locations for skyports (enabling pick-up of passengers to airport) within a city. Our approach is inspired from hub location problems, and our proposed method optimizes for aggregate travel time to multiple airports while satisfying the demand (trips to airports) either via (i) ground transportation to skyport followed by an air taxi to the airport, or (ii) direct ground transportation to the airport. The number of skyports is a constraint, and the decision to go via the skyport versus direct ground transportation is a variable in the optimization problem. Extensive experiments on publicly available airport trips data from New York City (NYC) show the efficacy of our optimization method implemented using Gurobi. In addition, we share insightful results based on the NYC data set on how ground transportation congestion can impact the demand and service efficiency in such skyports; this emerges as yet another factor in deciding the optimal number of skyports and their locations for a given city.

I. INTRODUCTION

Major cities around the world are currently struggling with a common problem: traffic congestion resulting from urban population growth. 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. Furthermore, in an extreme scenario, congestion can delay emergency services, i.e., delay in moving a critical patient to a medical center. Such concerns have pushed the transportation industry and academia to come up with new transportation modes. In this context, eVTOL (electric vertical takeoff and landing) vehicles, also known as air taxis [1], are emerging as a promising option to improve urban mobility.

Although air taxi services have not been launched yet in any major city, multiple industrial groups (including air manufacturers, large private companies, and smaller start-ups) are actively working on projects focused towards launching such services. For example, various technologies and regulatory steps associated with on demand mobility aircrafts have been recently discussed by NASA [2]; these include the use of distributed electric propulsion, noise and emission reduction, safety and reduction in operation and energy costs. In 2016, a white paper released by Uber [1] discussed their view on requirements of urban air taxis to make urban air mobility (UAM) feasible as an affordable solution to commuters. Such active interest and serious funding supporting air taxi projects is indicative of its (potential) widespread adoption in the near future. In addition, as a preliminary assessment of the impact of air taxi services, several groups have conducted surveys and analysis. For example, Rothfeld et al. [3] confirmed via simulations that the reduction in travel time will strongly influence the adoption of air taxi services. Another survey (conducted by Airbus) [4] spanning three regional groups (New York City, Frankfurt and Shanghai) indicated that airport transfers are the best use case for UAM adoption by commuters. This survey also indicated that the user’s willingness to pay for eVTOL technology is mostly driven by travel time reduction (i.e., for 50% travel time reduction, users are willing to pay about 2–2.5 times the taxi price (in USA and Germany) and 6 times the taxi price in China.

In this paper, we draw motivation from two key findings in the above surveys, which are in line with consumer expectations for air taxis: (i) reduction in travel time, and (ii) support for airport transfers. With such motivations, we focus on the problem of planning the infrastructure for air taxis for a given city, i.e., determining the location of skyports within the city. In particular, given a large city with multiple candidate skyport locations, it is non-trivial to select a small subset as skyports while optimizing for the end-to-end travel time vis-a-vis demand (trips) to nearby airports from multiple locations within the city. An additional layer of complexity in this problem is added by the flexibility of users to go via a skyport or via direct ground transportation (depending on which is faster) to their destination airport. The example described below explains these challenges in the context of a real city (NYC).

Illustrative example: Consider a person in Astoria (Queens, NYC) planning to go to any one of the nearby airports: JFK, Newark (EWR), and LaGaurdia (LGA) as shown in Figure 1. The table in Figure 1 shows the average travel time via ground transportation (e.g., taxi) from this location to the airports (inferred using real data from NYC, discussed later in the paper). If
there was a skyport located at UN/Turtle south bay (as shown in Figure 1), then it can be shown that the ground transportation to the skyport, followed by an air taxi trip (to the airport from the skyport) incurs significantly less travel time for JFK and EWR. For LGA a direct trip via ground transportation is still the fastest option. In general, while planning the location of (multiple) skyports in a city to reduce the end-to-end travel time to airports, one needs to consider the intricacies depicted in this example (multiple airports and routing based on fastest mode) in addition to the demand (trip counts) from each location in the city to the airports.

| airport       | ground transport | connection | commute time |
|---------------|------------------|------------|--------------|
| origin        |                  |            |              |
| Newark        | 57 min           | via skyport| 25.6 min     |
| JFK           | 34 min           | via skyport| 25.8 min     |
| LaGuardia     | 14 min           | direct     | 14 min       |

Fig. 1. Illustrative example of a skyport in NYC, and the resultant travel times to nearby airports, i.e., JFK, EWR (Newark), and LGA (LaGuardia) from a given location (Astoria) in Queens. Despite the skyport, a direct trip via ground transportation to LGA is the fastest option for this location, while for JFK and EWR, using the skyport can significantly reduce the travel time.

In this paper, we solve a generalization of the skyport planning problem discussed in the above example. In particular, for a city with a discrete set of potential locations for setting up skyports, our goal is to select a subset of locations to minimize the end-to-end travel time to airports under multiple constraints as depicted in the above example. We formulate this problem as a variant of the hub location problem (HLP), which is essentially an integer programming formulation. Our main contributions can be summarized as follows.

1) For a given city characterized by a discrete set of locations, and multiple airports associated with it, we formulate the air taxi skyport location problem as a variant of discrete HLP. The number of skyports is a constraint in the formulation, and for each airport trip origin (location), the decision to go to an airport via a skyport or via direct ground transportation is a decision variable in the optimization problem. In addition, our analysis considers sensitivity to varying ground transportation travel times and transfer times to the skyports to study how it changes the choice of optimal skyport locations.

2) Given the origin-demand matrix for multiple locations in the city (including associated airports), we implement the above optimization problem (using the Gurobi optimization tool [5]) on the first case study of NYC with real data to provide insights for air taxi development.

To the best of our knowledge, we are the first to model the skyport location problem for air taxis in the broader HLP framework, and implement a solution using Gurobi on real trips data. Although we demonstrate results for NYC, our method is fairly general, and can be applied to other cities selected for air taxi operations.

The remainder of this paper is organized as follows. Section II covers related work (including prior work on UAM, and HLP) and highlights gaps in the same with respect to our setup. The proposed methodology is described in Section III. This is followed by Section IV on experimental results, and we end the paper with a conclusion in Section V.

II. LITERATURE REVIEW

In this section, we first identify research gaps in the current literature about eVTOL location planning. To address such gaps, we leverage an existing optimization framework, i.e., HLP, and cover relevant prior work related to HLP in the following subsection.
A. Prior work on eVTOL and research gaps

In this subsection, we first describe the recent industry research surrounding eVTOLs followed by prior work on eVTOL infrastructure planning.

Industry interest and research: In general, eVTOLs have been an area of active investment for various air manufacturers and service companies (e.g., City Bus, Volocopter, Lilium Jet, EHang, Joby Aviation, Kitty Hawk) who have been pushing for its public acceptance. Aurora Flight Sciences and Pipistrel recently discussed their progress towards developing autonomy and eVTOL vehicles in partnership with Uber at the Uber Elevate Summit 2018 ([6], [7]). As a result of the summit, several operating guidelines for eVTOLs (air taxis) were issued as listed below

- eVTOL operating height during cruise phase: 1000 ft,
- eVTOL cruise speed: 150 miles/hour,
- eVTOL capacity: 3-4 passengers,
- touchdown and liftoff area (TLOF) maximum dimension: 45 ft,
- final approach and takeoff (FATO) maximum dimension: 70 ft, and
- safety area maximum dimension: 100 ft.

These dimensions take into consideration the largest possible aircraft dimensions in UAM and FAA guidelines [8]. As a proof that it is possible to have air taxis that can operate within these guidelines, Bell (in partnership with Uber) recently introduced a four seater hybrid electric propulsion powered air taxi prototype [9]. In terms of cities for deploying air taxi services, Dallas and Los Angeles were recently chosen for Uber’s pilot program, and the search for a third city is in progress.

Infrastructure planning for eVTOLs: To enable air taxi operations, ground infrastructure is needed for takeoff and landing. In its white paper, Uber [1] identified ground infrastructure selection to be a major operation challenge. In this context, Uber proposed skyports (also called vertiports) for its flagship air taxi program entitled Uber Elevate. A skyport is a designated area for boarding and alighting passengers along with parking spaces, charging points, and maintenance personnel. As per Uber’s proposal, a skyport can accommodate a maximum of 12 eVTOLs. Utilization of existing helipads as well as rooftops of high-rise parking garages or buildings for eVTOL operations is a topic of active interest targeted at reducing the infrastructure cost [1].

In the academic research community, limited studies have been conducted on eVTOL infrastructure requirements and selection ([8], [10], [13], [14]). In particular, they focus on operational and infrastructure requirements, and constraints for UAM. 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). A recent work by Lim et al. [14] proposed selecting skyport locations by using the K-means clustering algorithm, and demonstrated results for the Seoul metro area. However, 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. In this paper, we propose a more general and principled optimization framework (based on HLP) for optimizing the locations of skyports in any given city. As mentioned before in Section I motivated by survey results, we focus on airport transfers as a use case and optimize skyport locations for reducing the end-to-end travel time to airport.

B. Related work on hub location problem

The problem setup in our study has fundamental connections with HLP. Hubs are special facilities that serve as trans-shipment or switching points in a many-to-many distribution network. The basic framework of HLP is to select the locations for hubs 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 in the network. The selected hubs can collect the demand (trips) originating from origin locations, transfer them between hubs, and allocate them to respective destinations. Depending on the objective, there can be three major variations to the HLP [15], [16]:

1) p-median (minimum),
2) p-center(minimax), and
3) covering problem,

where p is the number of hubs (typically an input parameter). In the p-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 problems which include service time are typically formulated as p-center or hub covering problems. While the objective in p-center problems is to minimize the maximum distance between origin and destination (O-D) pairs, the hub covering problem

1The survey in [4] 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.
focuses on maximizing the service coverage.

The first mathematical formulations of HLP were proposed by O’Kelly [17], while focusing on a study based on airline passenger networks. In the HLP literature, this formulation is referred to as a single allocation $p$-hub median problem. The first linear integer programming formulation of this quadratic model was proposed by Campbell [18]. Various linear models for HLP were later proposed by Ernst and Krishnamoorty [19], and Skorin Kapov et al. [20]. In addition to selection of hub locations, the allocation of demand is an important decision criterion in HLP. In this context, there are two major allocation strategies for hub location: (i) single allocation where each non hub node (i.e., origin point in a network) is allocated to one hub, and (ii) multiple allocation where O-D flows can be transferred via different pairs of hubs ([18], [20], [21]). The hub facilities can be further categorized as uncapacitated (where there is no capacity restriction), and capacitated (where there is a limit to the maximum flow passing through a hub) ([22], [23]). Farahani et al. [24], Alumur and Kara [25] provide brief review and classification of various models and approaches to HLP.

In this paper, we focus on the single allocation $p$-hub median formulation. The $p$-hub median problem is known to be an NP-hard problem. In an attempt to solve larger problems with fewer variables and constraints, various attempts have been made to provide efficient solution algorithms. Such solution approaches (both exact and heuristics) for $p$-hub median problems include branch and bound, Lagrangian relaxation, simulated annealing, tabu search, lower bounding, branch and cut, genetic algorithm and modified Benders algorithm ([16], [19], [20], [22], [23], [26]–[30]). So far, many variations and approaches to the problem have been studied, and this is still an area of active research. However, no study has yet applied HLP to the air taxi skyport location problem.

III. METHODOLOGY

In this section, we first provide a high level overview of our approach using terminology which is fairly common in the HLP literature. This is followed by the formal problem formulation of the skyport location problem.

A. High level overview

With reference to the terminology used in the HLP literature (discussed in Section [II-B]), we model the skyport location problem as an uncapacitated single allocation $p$-hub median location problem (U-SA-M-p-HLP) with additional constraints (described below). The $p$-hub median problem is a specific type of discrete location model where $p$ hubs are chosen such that the choice minimizes the total travel cost for demand (trips from origin to destination nodes) via $p$ hubs. In this context,

- **single allocation** refers to the constraint that demand at each origin node is satisfied via a single hub,
- **being uncapacitated** allows the hubs to have infinite capacity (to accommodate incoming and outgoing trips),
- as a variation of the standard HLP formulation, we allow demand from an origin to either go via a hub (skyport) or via a direct route to the destination (i.e., routing capability),
- we do not consider any budget constraints or fixed infrastructure cost, and
- we do not consider interhub transfers.

In the remainder of this paper we use the term hub and skyport interchangeably.

B. Problem formulation

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

1) Setup: We assume that we have a discrete set $L$ consisting of $N$ locations spread across a given city. Without any loss of generality, the locations are indexed such that $L = \{1, 2, 3, \ldots, N\}$. We also have an O-D matrix (i.e., origin-destination matrix) corresponding to trips from a location $x \in L$ to an airport $y \in J$, where $J$ is the set of airports in the city (discrete set of size $N_{\text{dest}} \geq 1$). In other words, we only focus on trips which have an airport in set $J$ as their destination. As discussed in the overview in Section [III-A] we also consider routing capability in our setup, i.e., demand at each node can be routed either via a skyport to the destination airport or via direct ground transportation to the destination airport (as shown in Figure 2 the costs which are mentioned in the figure are explained below). Before describing the parameters and decision variables in the proposed optimization problem, we introduce additional notation as described below:

- index of origin: $i \in L$,
- index of destination: $j \in J$, and
- index of hub (skyport): $k \in L$.

The existing landing space for helicopters in airport zones are assumed to serve as landing zones for air taxis in our setup.
Fig. 2. Routing options for demand from an origin $i$ to destination airport $j$. The demand can be either satisfied via a single hub ($k$ allocated to $i$) incurring cost $c_{ik} + c_{kj}$ or via direct ground transportation incurring cost $c_{ij}$.

2) Parameters: The set of parameters fed as input to the proposed optimization problem can be listed as follows:

- $c_{ik} \triangleq$ ground transportation travel cost between origin $i$ and hub $k$ with $i, k \in \mathcal{L}$ and $c_{ik} \geq 0$,
- $c_{kj} \triangleq$ aerial travel cost from hub $k$ to destination airport $j$ with $k \in \mathcal{L}$, $j \in \mathcal{J}$, and $c_{kj} \geq 0$,
- $d_{ij} \triangleq$ demand originating from $i$ to destination airport $j$ with $i \in \mathcal{L}$, $j \in \mathcal{J}$, and $d_{ij} \in \mathbb{N} = \{1, 2, 3, 4, 5, \ldots \}$
- $c_{ij} \triangleq$ direct ground transportation travel cost from origin $i$ to destination $j$ with $i \in \mathcal{L}$, $j \in \mathcal{J}$, $c_{ij} \geq 0$ and,
- $p \triangleq$ number of hubs.

3) Decision variables: The binary decision variables $y_k$ (indicating if $k \in \mathcal{L}$ is a hub), $x_{ijk}$ (indicating use of hub $k$ for trip from $i$ to $j$), and $z_{ij}$ (indicating if demand from $i$ to $j$ is satisfied without a hub) are as formally described below.

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

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

$$z_{ij} = \begin{cases} 1 & \text{if demand at origin } i \text{ for destination } j \text{ is satisfied without a hub (direct connection)}, \\ 0 & \text{otherwise}. \end{cases}$$
4) Optimization problem: Using the notation defined in the previous subsections, we can now state the skyport location problem as an optimization problem (integer linear programming):

\[
\begin{align*}
\min & \quad \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{L}} (c_{ik} + c_{kj})d_{ij}x_{ijk} + \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{J}} c_{ij}d_{ij}z_{ij} \\
\text{s.t.} & \quad \sum_{j} \sum_{k} x_{ijk} = 1 - \sum_{j} z_{ij}, \quad \forall i \in \mathcal{L} \\
& \quad x_{ijk} \leq y_k \quad \forall i, k \in \mathcal{L}, \; j \in \mathcal{J} \\
& \quad \sum_{k} y_k = p \\
& \quad x_{ijk}, y_k, z_{ij} \in \{0, 1\} \quad i, k \in \mathcal{L}, \; j \in \mathcal{J}
\end{align*}
\] (4)

The objective function (4) captures the travel cost for each origin destination pair in the case when both direct connection and traveling via hub is allowed. Constraint (5) ensures that demand for each destination \(j\) at a non-hub node \(i\) is either satisfied via a hub located at \(k\) or by direct connection, while constraint (6) ensures single allocation (i.e., each non-hub node that passes through a hub is allocated to only one hub node). Constraint (7) ensures that the total number of hubs to be located is \(p\). In our approach, we allow direct connection from non-hub nodes to the destination. If the objective value achieved by adding the direct travel cost (from a node to a destination) is lower than considering the travel cost via a hub, then a direct connection is used to satisfy the node demand (for that O-D pair).

5) Incorporating transfer time and sensitivity to traffic delays: The concept of UAM utilizes the idea of a multimodal trip, which includes first mile access via a certain mode (on ground) and then switching to air taxi. Hence, there will be an additional transfer time required to switch between different modes. Also, the travel cost for ground transportation may increase due to additional congestion. We are interested to study the change in (optimal) hub locations and the demand for those hubs with respect to transfer time and traffic delays. In order to account for these effects, we include two additional factors in our formulation as described below:

- transfer time \((\alpha \geq 0)\), i.e., the time required to switch between one mode to the other along with access time to the rooftop of the skyport, and
- congestion factor \((\beta \geq 1)\) representing the relative increase in travel cost due to congestion (with \(\beta = 1\) denoting the prevailing ground transportation condition).

The formulation in Section III-B4 can be modified by accounting for the above factors, resulting in the following optimization problem:

\[
\begin{align*}
\min & \quad \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{L}} (\beta c_{ik} + \alpha + c_{kj})d_{ij}x_{ijk} + \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{J}} \beta c_{ij}d_{ij}z_{ij} \\
\text{s.t.} & \quad \sum_{j} \sum_{k} x_{ijk} = 1 - \sum_{j} z_{ij}, \quad \forall i \in \mathcal{L} \\
& \quad x_{ijk} \leq y_k \quad \forall i, k \in \mathcal{L}, \; j \in \mathcal{J} \\
& \quad \sum_{k} y_k = p \\
& \quad x_{ijk}, y_k, z_{ij} \in \{0, 1\} \quad i, k \in \mathcal{L}, \; j \in \mathcal{J}
\end{align*}
\] (9)

As shown above, all other constraints remain the same as in our previous formulation, and the objective function (9) is the overall travel cost by including transfer time and congestion factor.

We implement the solver for the optimization problem in (9) using the Gurobi optimization tool (version 8.1.0) [5]. For integer programming problems, Gurobi uses multiple heuristic approaches, e.g., parallel branch-and-cut algorithms, non-traditional tree-of-trees search algorithms, cutting plane methods, and symmetry detection.
IV. DATA SET AND EXPERIMENTAL RESULTS

In this section, we describe our data sets 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.

A. Data set and tools

1) Data set: Our study area includes five boroughs in NYC (The Bronx, Manhattan, Queens, Brooklyn and Staten Island) that are divided into 263 taxi zones \([31]\); each taxi zone has a unique zone ID. The centroids of the taxi zones are the trip origin nodes (locations) for our study, and trip destinations are the three major airports in NYC, i.e., EWR (Newark), JFK and LGA (LaGuardia). In our experiments, we consider the NYC taxi and limousine commission FHV (for-hire-vehicles) trip record data \([32]\) for January 2018. This is a publicly available data set, and the motivation for using FHV trips data for airport transfer is derived from the study in \([33]\) \(^3\) In this data set, 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 LGA (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.

2) Calculation of demand and travel costs: The input to our skyport location problem comprises of total trips to each airport from each taxi zone, and the associated travel cost for trips across taxi zones (including airports). The travel cost for a trip is assumed to be the average travel time (in minutes) from the origin taxi zone to the destination taxi zone (inferred from the FHV data set). In particular, the parameters defined in Section III-B2 are computed as follows:

- \(c_{ik}\) = average travel time from taxi zone \(i\) to zone \(k\) via ground transportation (inferred using FHV data set),
- \(c_{ij}\) = average travel time from taxi zone \(i\) to (airport) taxi zone \(j\) via ground transportation (inferred using FHV data set),
- \(c_{kj}\) = aerial travel time from taxi zone \(k\) to airport \(j\) computed using the latitude and longitude of locations \(k\) and \(j\) assuming Euclidean distance with a constant air taxi speed of 150 miles per hour.

The total airport demand, and travel costs were calculated using a script written in Python programming language (version 2.7.14). 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 destination taxi zone IDs: 1, 132 and 138) were selected, and used to compute the demand \(d_{ij}\) from origin \(i\) to destination airport \(j\).

To compute the travel time of a trip from one taxi zone to another, the time difference (i.e. end time - start time) for every trip was computed in minutes; the associated travel cost was then computed by averaging the travel time across multiple trips in the data set for the same origin-destination pair.

3) Data pruning: To further prune our data set, we filter out taxi zones which do not have significant demand for airports. The filtering process was implemented as follows. The demand data \(d_{ij}\) (as explained in Section IV-A2) was used to generate a choropleth map in ArcMap (version 10.5.1) \([34]\) as shown in Figure 3. As shown in the map, the 263 taxi zones can be divided into six categories (based on the fraction of total airport trips originating from a taxi zone). For our experiments, we excluded the taxi zones with the lowest fraction of trips (first category in the choropeth map), and as a result we focused on the remaining 144 taxi zones (i.e., the top 144 zones contributing to airport trips). Hence, as per the notation defined in Section III-B1 \(|L| = 144\) and \(|J| = 3\) (i.e., three airports).

4) Tools: To solve the proposed optimization problem (as described in Section III-B5), Gurobi optimization tool (version 8.1.0) and Python programming language (version 2.7.14) were used. Based on 144 taxi zones and 3 airports, the optimization problem for NYC consisted of 62784 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 5 seconds (for solving an instance of the optimization problem in Gurobi for the above data set).

B. Optimization results

Using the travel cost, and demand data obtained for 144 taxi zones (as described in Section IV-A3), we computed optimal skyport locations using our proposed optimization problem described in Section III-B5. For the transfer time factor \(\alpha\), we considered four possible values i.e. 0, 10, 15, and 20 minutes. For the congestion factor \(\beta\), we considered two possible values: \(\beta = 1\) (prevailing ground transportation travel cost), and \(\beta = 1.1\) (for a 10% increase in ground transportation travel cost due to congestion). Seven different combinations of \((\alpha, \beta)\) were considered for our experiments (as listed below).

1) \(\alpha = 0, \beta = 1\) (base case: no transfer time and no congestion)
2) \(\alpha = 10, \beta = 1\)

\(^3\)This study \([33]\) indicated that 42% of trips to JFK are via FHV and taxis.
Fig. 3. Choropleth map showing the taxi zone-wise demand for the three airports in NYC with zone shading.

| number of skyports (p) | objective value (vehicles-minutes) in millions | % decrease w.r.t. \( p = 0 \) | Gurobi iterations | computation time (seconds) | # direct connections \( (z_{ij}) \) | skyport location (taxi zone) IDs |
|------------------------|-----------------------------------------------|-------------------------------|-------------------|--------------------------|---------------------------------|-------------------------------|
| 0                      | 19.53                                        | -                             | -                 | -                        | -                              | -                             |
| 1                      | 11.62                                        | 40.50                         | 20277             | 3.99                     | 149                            | 233                           |
| 2                      | 10.36                                        | 51.74                         | 18364             | 4.01                     | 101                            | 80, 233                       |
| 3                      | 9.42                                         | 67.14                         | 15322             | 3.65                     | 91                             | 80, 107, 142                 |
| 4                      | 8.82                                         | 74.88                         | 13252             | 4.51                     | 94                             | 49, 233, 238, 249            |
| 5                      | 8.31                                         | 80.86                         | 9850              | 3.25                     | 83                             | 80, 181, 233, 238, 249       |
| 6                      | 8.03                                         | 85.86                         | 9646              | 4.41                     | 83                             | 80, 161, 181, 233, 238, 249  |
| 7                      | 7.78                                         | 90.16                         | 9412              | 4.64                     | 79                             | 61, 87, 90, 112, 161, 233, 238|
| 8                      | 7.53                                         | 94.62                         | 8483              | 3.30                     | 66                             | 7, 61, 80, 87, 90, 161, 233, 238|
| 9                      | 7.29                                         | 97.67                         | 7785              | 3.13                     | 65                             | 7, 61, 80, 87, 90, 161, 233, 238|
| 10                     | 7.07                                         | 99.80                         | 7529              | 2.98                     | 65                             | 7, 61, 80, 87, 90, 161, 233, 238, 263|

TABLE I
OPTIMIZATION RESULTS FOR BASE CASE SCENARIO.

3) \( \alpha = 10, \beta = 1.1 \)
4) \( \alpha = 15, \beta = 1 \)
5) \( \alpha = 15, \beta = 1.1 \)
6) \( \alpha = 20, \beta = 1 \)
7) \( \alpha = 20, \beta = 1.1 \)

For each of the cases listed above, 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). The results include the (optimized) objective value, number of iterations, computation time, and the hub locations (for a given value of \( p \)). In addition, for each case we obtained the list of non-skyport locations for which the demand is routed either via direct ground transportation or via an allocated skyport.

The results obtained for different values of \( p \) for the base case scenario (\( \alpha = 0, \beta = 1 \), i.e., no transfer time and no congestion) are summarized in Table I. Objective function values (after optimization) are reported as the exact trip-time values.
(vehicles-minutes) without any scaling.

Fig. 4. Comparison of the (optimized) objective function values for different values of transfer time $\alpha$, and congestion factor $\beta$. The shown objective function value for each choice of $(\alpha, \beta)$ is normalized with respect to the value at $p=0$.

Fig. 5. Comparison of number of direct connection to airports (i.e., the number of (origin, destination airport) pairs not assigned to skyports) for different values of transfer time and congestion factor.

As shown in Table I, with each additional skyport, the objective value monotonically decreases. Table I also reports (as direct connections) the number of (origin, destination airport) pairs which were not assigned a skyport. For example, for the case of $p = 10$, only 65 such pairs (out of 144 × 3 possible pairs) were not assigned a skyport. As shown in Table I, the number of such direct connections also decreases steadily up to $p = 8$, after which the decrease is not significant. The optimization results for other choices of $(\alpha, \beta)$ are reported in Appendix A. In addition, the optimality gap reported by Gurobi for our experiments spanning different choices of $(\alpha, \beta)$ was zero.

Figure 4 shows the variation of the optimized objective value across different choices of $(\alpha, \beta)$, i.e., the transfer time and ground transportation congestion. As shown in the figure, with an increase in the transfer time, the optimal objective value curve shifts further (upwards) from the curve for the base case scenario $(\alpha = 0, \beta = 1)$. In addition, the objective values for the case with $\beta = 1.1$ (additional congestion), are observed to be lower than those for the case of $\beta = 1$. In a similar spirit, Figure 5 shows the number of direct connections (as defined for Table I above) after the optimization for $p$ skyport locations for different choices of $(\alpha, \beta)$. As shown, the number of direct connections increases with an increase in transfer time. Also,
Fig. 6. Allocation of demand to three airports in NYC via $p = 6$ skyports (for $\alpha = 15$ and $\beta = 1$). The edges connecting the trip origins to skyports are color coded for the three different destination airports.

the number of direct connections decrease with an increase in congestion, implying that routing via skyports during congestion can reduce the overall travel time.

Finally, to get a sense of the optimal skyport locations, Figure 6 shows a visualization (created using ArcMap) for $p = 6$.

C. Demand at each skyport

As an outcome of the optimized skyport locations (as discussed in Section IV-B), it is possible to estimate the (incoming) demand at each skyport; this demand corresponds to the trips to airports which were routed to a skyport from an origin. In this subsection, we study the characteristics of such demand vis-a-vis the number of skyport locations. In particular, we compute the following aggregates.

- For each skyport location $k$, we compute the average number of (routed) incoming trips for every hour of the day. We will refer to this hour-wise aggregate as the daily demand profile of a skyport.
- We compute the peak value of the daily demand profile for a skyport location $k$, and denote it by $\lambda_k$.

For the case of $p = 6$, Figure 7 shows the daily demand profile for the 6 skyport locations optimized for the case of $\alpha = 15$ minutes (transfer time) and $\beta = 1.1$ (congestion). As shown, there are two peaks (one around 6 – 7 A.M. and the other around 3 – 5 P.M.) across the 6 skyports. For further analysis, for each choice of $p$, we define $\lambda_p^{\text{max}}$ as the maximum value of $\lambda_k$ across the $p$ skyports. In a sense, this is the maximum hourly rate of arrival across $p$ skyports during the entire day. Figure 8 shows this maximum rate of arrival for different values of $p$ and choices of $(\alpha, \beta)$ (additional details are in Appendix B). As shown, the variation in $\lambda_p^{\text{max}}$ (for a given value of $p$) due to different choices of $(\alpha, \beta)$ is significantly higher for lower values of $p$. Such sensitivity to $(\alpha, \beta)$ variations decreases as $p$ increases (with minimum variation observed at $p = 9$).

D. Market penetration

In this subsection, we describe a queuing theoretic analysis to estimate the proportion of demand that can be handled at the selected skyport locations. In particular, if the skyports have a limited number of air taxis, the users (demand) arriving via ground transportation at the skyport may have to wait (in a queue) until an available air taxi (server) picks them up, and

For each trip in the data set, we add the trip start time and the estimated travel time to the allocated skyport, and determine the total number of incoming trips for the skyport in a given hour of the day.
Fig. 7. Daily demand profile for skyports in the case of $p = 6$, $\alpha = 15$, and $\beta = 1.1$

Fig. 8. Comparison of maximum arrival rate ($\lambda_p^{\text{max}}$) at skyports for different values of $p$ and choices of $(\alpha, \beta)$.

transports them to the destination. If we assume a hard constraint on the tolerable wait time in the queue (in addition to the transfer time), we can compute the service efficiency (market penetration) of a skyport as the fraction of demand that can be served within the wait time constraint. For market penetration estimation the following assumptions were considered:

- air taxi fare is the same as regular (ground transportation) taxi fare (this assumption serves as an upper bound for market penetration),
- users are not willing to wait longer than 5 minutes (wait time constraint), and
- users do not consider rerouting to other less crowded skyports (i.e., they would take ground transportation in that case).

These assumptions are useful towards understanding how the potential demand at a skyport is constrained by the number of available air taxis, and the wait time in the service queue; this is an important factor in evaluating any low capacity, high performance system like air taxis. In addition to the points mentioned above, other assumptions may be made as follows. We describe a worst-case analysis below for service efficiency using the maximum arrival rate at skyports (i.e., $\lambda_p^{\text{max}}$ as estimated in the previous subsection), and $M/M/c$ queue assumptions [35]–[37] (as explained below).

Queue analysis overview: Assuming each skyport as a queuing system, we require the following parameters for our $M/M/c$ queue analysis:

- number of servers $c$ at the skyport (assumed to be 12 as per Uber Elevate specifications [1]),
- service rate $\mu$ (computed below), and
- arrival rate $\lambda$.  


Given a wait time constraint, $c$, and $\mu$, it is possible to compute the maximum tolerable $\lambda = \lambda^{tol}$ under the $M/M/c$ queue assumptions. Specifically, the average wait time in a queue (i.e., $W_q$), $\lambda$, $c$ and $\mu$ are related as shown below [37]:

$$W_q = \frac{L_q}{\lambda},$$  \hspace{1cm} (14)

$$L_q = P_0 \left( \frac{\lambda}{\mu} \right)^c \frac{\left( \frac{\lambda}{\mu} \right)^c}{c! \left( 1 - \frac{\lambda}{\mu} \right)^2},$$ \hspace{1cm} (15)

$$P_0 = \sum_{n=0}^{c-1} \frac{\left( \frac{\lambda}{\mu} \right)^n}{n!} + \frac{\left( \frac{\lambda}{\mu} \right)^c}{c! \left( 1 - \frac{\lambda}{\mu} \right)^2} \right]^{-1},$$  \hspace{1cm} (16)

where $L_q$ is the average length of the queue, and $P_0$ is the probability of an empty queue. With the given values of $W_q$, $c$, and $\mu$, one can numerically solve for $\lambda = \lambda^{tol}$. After computing the maximum tolerable arrival rate $\lambda^{tol}$, the (worst case) market penetration at a skyport can be defined as:

$$\text{market penetration with } p \text{ hubs} = \frac{\lambda^{tol}}{\lambda_{max}^p}$$ \hspace{1cm} (17)

In simpler words, market penetration is the fraction of demand at a skyport that can be served subject to the wait time constraint. We describe the calculation details for the NYC setup below.

**Calculation details for NYC:** As stated before, we assume $c = 12$ (number of servers), and that one vehicle trip represents one passenger. The service time is the round trip time from the skyport to the airport including the time taken for loading and unloading passengers. In our context, a worst case estimate for the service time can be computed as follows. We compute the maximum value of aerial time computed ($\max_{k,j} c_{kj}$) in Section IV-A2 from a candidate skyport location to a destination airport (i.e., 10.22 minutes), and assume a loading-unloading time of 2 minutes (at each end). Thus, each air taxi requires about 24.44 minutes to serve one passenger; this gives a service rate $\mu = \frac{1}{24.44} \times 60 = 2.5$ vehicles/hour. Using the above values of $c$, $\mu$, and the (average) wait time of 5 minutes, $\lambda^{tol}$ obtained was 24 vehicles/hour. For each scenario in our study (i.e., different choices of $(\alpha, \beta)$), the market penetration was determined as the ratio of $\lambda^{tol}$ and $\lambda_{max}^p$ (in percentage) as defined in (17).

![Fig. 9. Market penetration for different values of $p$ and choices of $(\alpha, \beta)$](image)

**Discussion:** As shown in Figure 9 for lower values of $p$ the air taxis at a skyport can handle less than 10% of the maximum demand. As $p$ increases (i.e., $p \geq 9$), higher market penetration is observed. Note that the market penetration estimated for $p$ skyports is dependent on the wait time and service rate of the air taxis. It is possible that for passengers sharing the same destination, an air taxi serves more than one passenger at a time (as opposed to 1 passenger considered in the above calculation). In such a case, the market penetration achieved would be relatively higher. This observation that sharing a car to the skyport while going to a common destination airport can increase the skyport’s service efficiency is in line with the observations in another work on airport access [33]. In particular, the study on airport access via ground transportation in [33] observed a 11 – 14% increase in consumer surplus resulting from shared taxi policies. In this context, analysis of market penetration for air taxis (as shown above) can serve as a criteria for air taxi operating policies as well (such as batching of passengers sharing the same destination within the allowable wait time).
V. Conclusion

In this paper, we formulated a new skyport location optimization problem for access to special destinations like airports as a variant of HLP. Our 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. The objective of the optimization was to reduce the end-to-end travel time, while allowing the demand to be routed either via skyports or via direct ground transportation. The case study of NYC was presented considering airport 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. Our experimental results spanning different scenarios for transfer time (multimodal setup), and congestion provide insightful pointers which can guide planners and policy makers. One category of such insights is around the choice of number of skyports (p). The results for demand at each skyport (based on optimal skyport locations) show that for \( p \geq 6 \), there is not much variation in the incoming demand at skyport (across different transfer time and congestion factor choices). However, the market penetration results show that an even higher value i.e., \( p \geq 9 \) is required to achieve at least 10% market penetration. Such insights can further guide the budget allocations for air taxi infrastructure development.

In terms of future directions, our study can be further refined along the following lines:

- the optimization problem can be augmented by considering other modes of transportation (e.g., bike, walk, e-scooters, public transit),
- 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,
- developing robust optimization methods with additional heuristics, and
- queue sensitive air taxi rebalancing (motivated by similar work for ground transportation [38]).

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

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In this section, we report additional details from our experiments (for optimization results, maximum arrival rate and market penetration).

### A. Optimal skyport locations for different choices of \((\alpha, \beta)\)

In a spirit similar to the optimization results reported in Table I, Tables II, III, IV, V, VI, and VII report the results for cases \((\alpha = 10, \beta = 1), (\alpha = 15, \beta = 1), (\alpha = 20, \beta = 1), (\alpha = 10, \beta = 1.1), (\alpha = 15, \beta = 1.1), (\alpha = 20, \beta = 1.1)\) respectively.

| number of skyports \((p)\) | objective value (vehicles-minutes) | % decrease \(w.r.t. \ p = 0\) | Gurobi iterations | computation time (seconds) | # direct connections \((z_{ij})\) | skyport location (taxi zone) | IDs |
|-----------------------------|-----------------------------------|-------------------------------|-------------------|-----------------------------|-------------------------------|-----------------------------|-----|
| 0                           | 19.53                             | -                             | -                 | -                           | -                             | 233                          |     |
| 1                           | 15.22                             | 17.32                         | 15114             | 3.19                        | 219                           | 107                          | 123 |
| 2                           | 14.34                             | 20.86                         | 14397             | 3.01                        | 200                           | 96                          | 142 |
| 3                           | 13.63                             | 23.73                         | 11670             | 2.91                        | 148                           | 49                          | 107 |
| 4                           | 13.12                             | 25.77                         | 9369              | 2.73                        | 138                           | 49                          | 107 |
| 5                           | 12.78                             | 27.14                         | 7888              | 2.70                        | 123                           | 80                          | 181 |
| 6                           | 12.50                             | 28.26                         | 7081              | 2.59                        | 123                           | 80                          | 161 |
| 7                           | 12.26                             | 29.23                         | 6491              | 2.43                        | 121                           | 80                          | 181 |
| 8                           | 12.05                             | 30.05                         | 6703              | 2.30                        | 121                           | 80                          | 181 |
| 9                           | 11.86                             | 30.84                         | 6563              | 2.42                        | 117                           | 80                          | 181 |
| 10                          | 11.66                             | 31.62                         | 6150              | 2.54                        | 116                           | 79                          | 263 |

**TABLE II**

**OPTIMIZATION RESULTS FOR \(\alpha = 10\) AND \(\beta = 1\).**

### B. Maximum arrival rate details

Table VIII reports the \(\lambda_{p}^{\max}\) (veh/hour) for different choices of \((\alpha, \beta)\), and the associated variation across different choices of \((\alpha, \beta)\) for a given \(p\).

### C. Market penetration details

Table IX reports the market penetration \(\chi_{p}^{\text{vol}}\) (%) for different choices of \((\alpha, \beta)\) for a given \(p\).
| number of skyports (p) | objective value (vehicles-minutes) | % decrease w.r.t. p = 0 | Gurobi iterations | computation time (seconds) | # direct connections (z_{ij}) | skyport location (taxi zone) IDs |
|-----------------------|-----------------------------------|------------------------|------------------|--------------------------|-----------------------------|--------------------------------|
| 0                     | 24.88                             | -                      | -                | -                        | -                           | -                              |
| 1                     | 16.29                             | 34.54                  | 15782            | 3.43                     | 206                         | 233                            |
| 2                     | 15.29                             | 38.52                  | 15168            | 3.29                     | 189                         | 107, 142                       |
| 3                     | 14.44                             | 41.94                  | 11927            | 2.75                     | 139                         | 49, 107, 142                   |
| 4                     | 13.87                             | 44.25                  | 9890             | 2.78                     | 130                         | 49, 233, 238, 249              |
| 5                     | 13.47                             | 45.85                  | 7912             | 2.63                     | 115                         | 80, 181, 233, 238, 249         |
| 6                     | 13.17                             | 47.08                  | 7481             | 2.55                     | 115                         | 80, 161, 181, 233, 238, 249    |
| 7                     | 12.89                             | 48.17                  | 6610             | 2.40                     | 114                         | 80, 87, 90, 161, 181, 230, 233, 249|
| 8                     | 12.67                             | 49.08                  | 6900             | 2.57                     | 114                         | 80, 87, 90, 161, 181, 230, 233, 238 |
| 9                     | 12.45                             | 49.97                  | 6646             | 2.54                     | 111                         | 80, 87, 90, 161, 181, 230, 233, 238, 263 |
| 10                    | 12.23                             | 50.86                  | 6066             | 2.56                     | 100                         | 61, 80, 87, 90, 161, 181, 230, 233, 238, 263 |

**TABLE III**
Optimization results for $\alpha = 10$ and $\beta = 1.1$.

| number of skyports (p) | objective value (vehicles-minutes) | % decrease w.r.t. p = 0 | Gurobi iterations | computation time (seconds) | # direct connections (z_{ij}) | skyport location (taxi zone) IDs |
|-----------------------|-----------------------------------|------------------------|------------------|--------------------------|-----------------------------|--------------------------------|
| 0                     | 19.53                             | -                      | -                | -                        | -                           | -                              |
| 1                     | 16.65                             | 11.57                  | 11999            | 2.78                     | 277                         | 233                            |
| 2                     | 15.91                             | 14.56                  | 11631            | 2.59                     | 250                         | 161, 249                       |
| 3                     | 15.46                             | 16.36                  | 13118            | 2.99                     | 206                         | 142, 148, 170                  |
| 4                     | 15.02                             | 18.11                  | 8154             | 2.41                     | 178                         | 142, 181, 233, 249             |
| 5                     | 14.75                             | 19.19                  | 7704             | 2.72                     | 167                         | 80, 142, 181, 233, 249         |
| 6                     | 14.50                             | 20.23                  | 6828             | 2.25                     | 159                         | 80, 161, 181, 233, 238, 249    |
| 7                     | 14.26                             | 21.17                  | 5865             | 2.26                     | 156                         | 80, 87, 90, 161, 181, 230, 233, 238 |
| 8                     | 14.06                             | 21.99                  | 5676             | 2.34                     | 156                         | 80, 87, 90, 161, 181, 230, 233, 238 |
| 9                     | 13.88                             | 22.71                  | 5410             | 2.16                     | 150                         | 79, 80, 87, 90, 161, 181, 230, 233, 238 |
| 10                    | 13.71                             | 23.41                  | 5103             | 2.22                     | 140                         | 61, 79, 80, 87, 90, 161, 181, 230, 233, 238, 238 |

**TABLE IV**
Optimization results for $\alpha = 15$ and $\beta = 1.1$.
| number of skyports (p) | objective value (vehicles-minutes) | % decrease w.r.t. p = 0 | Gurobi iterations | computation time (seconds) | # direct connections (ziu) | skyport location (taxi zone) |
|------------------------|-----------------------------------|------------------------|-------------------|---------------------------|--------------------------|-----------------------------|
| 0                      | 19.53                             | -                      | -                 | -                         | -                        | -                           |
| 1                      | 17.71                             | 7.29                   | 8953              | 2.10                      | 327                      | 170                         |
| 2                      | 17.16                             | 9.54                   | 8340              | 1.97                      | 300                      | 161,249                     |
| 3                      | 16.86                             | 10.74                  | 11107             | 2.51                      | 279                      | 161,239,249                 |
| 4                      | 16.57                             | 11.90                  | 7778              | 2.10                      | 258                      | 87,90,161,239               |
| 5                      | 16.34                             | 12.84                  | 7186              | 2.03                      | 229                      | 87,90,161,181,239           |
| 6                      | 16.11                             | 13.73                  | 6281              | 1.89                      | 224                      | 87,90,161,162,181,239       |
| 7                      | 15.91                             | 14.53                  | 5681              | 1.98                      | 224                      | 87,90,161,162,181,230,239   |
| 8                      | 15.75                             | 15.19                  | 5661              | 1.93                      | 219                      | 79,87,90,161,162,181,230,239 |
| 9                      | 15.60                             | 15.80                  | 4682              | 1.97                      | 206                      | 79,87,90,161,162,181,230,239,255 |
| 10                     | 15.46                             | 16.35                  | 4404              | 1.95                      | 205                      | 79,87,90,161,162,181,210,239,255 |

**TABLE VI**
Optimization results for \( \alpha = 20 \) and \( \beta = 1 \).

| number of skyports (p) | objective value (vehicles-minutes) | % decrease w.r.t. p = 0 | Gurobi iterations | computation time (seconds) | # direct connections (ziu) | skyport location (taxi zone) |
|------------------------|-----------------------------------|------------------------|-------------------|---------------------------|--------------------------|-----------------------------|
| 0                      | 24.88                             | -                      | 10558             | 2.31                      | 314                      | 170                         |
| 1                      | 19.00                             | 23.61                  | 9731              | 2.10                      | 282                      | 161,249                     |
| 2                      | 18.30                             | 26.45                  | 9556              | 2.12                      | 255                      | 161,239,249                 |
| 3                      | 17.91                             | 29.54                  | 8232              | 2.09                      | 204                      | 161,181,239,249             |
| 4                      | 17.53                             | 30.65                  | 7554              | 2.09                      | 201                      | 87,90,161,181,239           |
| 5                      | 17.25                             | 31.64                  | 7055              | 2.22                      | 196                      | 87,90,161,162,181,239       |
| 6                      | 16.97                             | 32.52                  | 6601              | 2.34                      | 193                      | 87,90,161,162,181,230,239   |
| 7                      | 16.75                             | 33.39                  | 5327              | 2.06                      | 185                      | 87,90,161,162,181,230,239   |
| 8                      | 16.58                             | 34.12                  | 5257              | 2.02                      | 180                      | 79,87,90,161,162,181,230,239,255 |
| 9                      | 16.39                             | 34.81                  | 4626              | 2.18                      | 169                      | 61,79,87,90,161,162,181,230,239,255 |
| 10                     | 16.22                             | 35.50                  | -                 | -                         | -                        | -                           |

**TABLE VII**
Optimization results for \( \alpha = 20 \) and \( \beta = 1.1 \).

| number of skyports (p) | objective value (vehicles-minutes) | % decrease w.r.t. p = 0 | Gurobi iterations | computation time (seconds) | # direct connections (ziu) | skyport location (taxi zone) |
|------------------------|-----------------------------------|------------------------|-------------------|---------------------------|--------------------------|-----------------------------|
| 1                      | 910                               | 27.61                  | 10558             | 2.31                      | 314                      | 170                         |
| 2                      | 588                               | 24.55                  | 9731              | 2.10                      | 282                      | 161,249                     |
| 3                      | 513                               | 21.05                  | 9556              | 2.12                      | 255                      | 161,239,249                 |
| 4                      | 489                               | 18.65                  | 8232              | 2.09                      | 204                      | 161,181,239,249             |
| 5                      | 475                               | 16.25                  | 7554              | 2.09                      | 201                      | 87,90,161,181,239           |
| 6                      | 475                               | 13.85                  | 7055              | 2.22                      | 196                      | 87,90,161,162,181,239       |
| 7                      | 475                               | 11.45                  | 6601              | 2.34                      | 193                      | 87,90,161,162,181,230,239   |
| 8                      | 475                               | 9.05                   | 5327              | 2.06                      | 185                      | 87,90,161,162,181,230,239   |
| 9                      | 475                               | 6.65                   | 5257              | 2.02                      | 180                      | 79,87,90,161,162,181,230,239,255 |
| 10                     | 475                               | 4.25                   | 4626              | 2.18                      | 169                      | 61,79,87,90,161,162,181,230,239,255 |

**TABLE VIII**
Maximum arrival rate \( \lambda_p^{\text{max}} \) (veh/hour) for different choices of \( (\alpha, \beta) \), and the associated variation across different choices of \( (\alpha, \beta) \) for a given \( p \).
| number of skyports (p) | $\alpha=10$, $\beta=1$ | $\alpha=10$, $\beta=1.1$ | $\alpha=15$, $\beta=1$ | $\alpha=15$, $\beta=1.1$ | $\alpha=20$, $\beta=1$ | $\alpha=20$, $\beta=1.1$ |
|-----------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| 1                     | 2.64                    | 2.56                    | 3.25                    | 3.03                    | 4.31                    | 3.88                    |
| 2                     | 4.10                    | 4.08                    | 5.26                    | 4.55                    | 6.06                    | 5.97                    |
| 3                     | 4.68                    | 4.71                    | 6.78                    | 5.07                    | 6.92                    | 6.92                    |
| 4                     | 4.91                    | 4.91                    | 6.67                    | 6.58                    | 8.42                    | 6.94                    |
| 5                     | 5.05                    | 5.04                    | 6.90                    | 6.74                    | 8.42                    | 8.42                    |
| 6                     | 8.82                    | 8.54                    | 8.92                    | 8.84                    | 9.88                    | 9.16                    |
| 7                     | 9.72                    | 9.38                    | 10.67                   | 10.26                   | 9.88                    | 10.91                   |
| 8                     | 9.72                    | 9.38                    | 10.67                   | 10.26                   | 12.12                   | 9.16                    |
| 9                     | 10.67                   | 10.91                   | 12.50                   | 12.50                   | 12.12                   | 11.54                   |
| 10                    | 12.50                   | 10.91                   | 12.50                   | 12.50                   | 16.90                   | 11.54                   |

**TABLE IX**

Market penetration $\frac{X_{tol}}{X_p}$ (%) for different choices of $(\alpha, \beta)$ for a given $p$. 