Abstract—Current proposals for advanced air mobility (AAM) propose that third-party service providers (SPs) will be responsible for providing traffic management services for these aircraft. This paper examines two aspects of these proposals, namely that: 1) multiple SPs can operate in the same region of airspace, competing for the patronage of AAM fleet operators, and 2) SPs can themselves be fleet operators. To this end, we propose and analyze a three-tier economic model of competition between traffic management SPs. We consider several potential scenarios, including a monopolistic SP, multiple competing SPs, the presence of a public option, and a service provider who is also a fleet operator. Our analysis suggests that in the absence of excessive congestion, an SP can also be a fleet operator without significantly distorting the economic outcomes. Furthermore, we find that under certain reasonable assumptions, the presence of a public option SP can improve consumer surplus while at the same time allowing private SPs to be profitable.

Keywords—economics of advanced air mobility; traffic management service providers; competition; public option

I. INTRODUCTION

The emergence of advanced air mobility (AAM) operations, including urban air mobility (UAM) and uncrewed aerial systems (UAS), are expected to transform the air transportation system landscape. A parallel transformation is also imminent in air traffic management, with the FAA and other Air Navigation Service Providers (ANSPs) declaring that they will not be providing traffic management services for AAM. Instead, it is expected that private, third-party service providers (SPs) will be responsible for managing AAM traffic [1].

The proposed architecture for AAM is that of a federated network of third-party (private) service providers, although public sector SPs may also exist [2]. Furthermore, it is expected that multiple SPs may have overlapping geographical service regions and that some SPs may operate their own aircraft fleets [1]. In recent work, we showed that it was possible to design profit-sharing mechanisms that incentivized competing SPs in a federated network to cooperate to improve efficiency [3]. However, questions remained on what would happen if SPs competed for the patronage of fleet operators in the same airspace, and what would happen if an SP was also allowed to operate its own aircraft in the region. A related question was whether a public sector SP (i.e., the public option) was necessary in these situations. This paper aims to address these open questions.

A. Related work

Models of pricing and competition for air transportation resources have been previously studied in the context of airports [4]–[8], flight routes [9], [10], and even ANSPs [11]. A key difference between these settings and AAM traffic management is that they deal with a more mature aviation industry with well-established economic models, less inter-service provider competition, and no concerns of service providers also operating fleets and potentially stifling their competition.

Stronger comparisons may be drawn between AAM service providers and the evolution of Internet Service Providers [12]. For example, multiple Internet Service Providers (ISPs) operate and compete in last-mile Internet traffic delivery to users in dense urban areas. A SP that is also an operator is analogous to how some ISPs are vertically integrated with content providers (e.g., Comcast and NBC) and are accused of preferentially handling their own traffic. More broadly, concerns about SPs handling traffic from different fleet operators unequally parallels the debate around net neutrality. Prior work has studied the possibility of improved investment in capacity by ISPs who are also content providers when they are paid by dedicated content providers [13], as well as the provision of differentiated service classes based on payment [14]. Studies have also shown that consumer welfare and profit are not entirely at odds with each other [15]. Finally, the introduction of a public option ISP that
provides a free, basic service for all users has been shown to curtail monopoly ISPs and improve consumer welfare [16].

Much of the work on Internet economics assumes that capacity is unconstrained, i.e., more capacity can be provided through an infrastructure investment such as a new fiber optic line. By contrast, we assume that AAM airspace capacity is a limited resource. This assumption, in addition to the models of delay costs and consumer valuations for AAM traffic, differentiate our work from prior efforts.

B. Outline

In Sec. II, we propose a three-tier model of the AAM airspace, with the airspace authority, service providers and fleet operators. We use this model analyze a monopoly SP in Sec. III, both when the SP is not also an operator, and when it is one. In Sec. IV, we study inter-SP competition, introduce a public option SP, and study SP behavior when it is also an operator in these settings. We conclude with promising future directions in Sec. V.

II. Proposed Model

| TABLE I: Notation used in our airspace model. |
|-----------------|-----------------|-----------------|
| \( \mathcal{P} \) | Set of all SPs \{ \( P_0, P_1, \ldots, P_{N_0} \) \} | \( c_i \) | Airspace capacity requested by \( P_i \) |
| \( \mathcal{O} \) | Set of all operators \{ \( O_1, O_2, \ldots, O_{N_o} \) \} | \( p_i \) | Price per unit flight charged by \( P_i \) |
| \( r_j \) | Valuation per unit flight by \( O_j \) | \( \hat{q}_j \) | Desired number of flights by \( O_j \) |
| \( f_j \) | Flight distribution \( (f_j^1, f_j^2, \ldots, f_j^{N_j}) \) of operator \( O_j \) | \( q_j^i \) | Number of flights operated by \( O_j \) with \( P_i \) |
| \( \pi_j^i \) | Reward per unit flight for \( O_j \) partnered with \( P_i \) | \( S_j \) | Consumer surplus of \( O_j \) |
| \( R_i \) | Profit for \( P_i \) | \( \hat{x}_i \) | Total flights requested to \( P_i \), namely, \( \sum_j f_j^i \hat{q}_j \) |
| \( \beta^i(\hat{x}_i, j) \) | Allocation mechanism for \( P_i \) | \( \alpha_i \) | Multiplicative constant on delay for \( P_i \), namely, \( (x_i/\alpha_i)^2 \) |
| \( k_{\text{infra}}(\alpha_i) \) | Infrastructure cost for \( P_i \), assumed to be of the form \( k/\alpha_i \) | \( b \) | Cost per unit of airspace set by the airspace authority |

1) Airspace model: We consider a region of airspace, which we define as having a total capacity \( c = 1 \). The total capacity can be thought of as the volume of physical airspace available. This airspace is a divisible resource initially controlled by an airspace authority, that can be distributed to service providers, and by them to operators. There are \( N_o \) SPs that would like to operate in the airspace, while SP \( P_i, i \in \{1, \ldots, N_o\} \) (which we will refer to as the set \( \mathcal{P} \) ) buys or receives a capacity \( c_i \in [0, 1] \) from the airspace authority, such that \( \sum_{P_i \in \mathcal{P}} c_i = 1 \). The \( b \) is the cost per unit airspace set by the airspace authority, each SP pays \( bc_i \) to the airspace authority, which earns total fees of \( A = \sum_{i=1}^{N_0} bc_i \).

Additionally, there are \( N_o \) operators of AAM flights; each operator \( O_j, j \in \{1, \ldots, N_o\} \) (which we will refer to as at the set \( \mathcal{O} \) ) has a valuation \( v_j \in [0, 1] \) per unit flight. \( O_j \) would like to operate a desired number of flights \( \hat{q}_j \in \mathbb{R}^+ \) flights, but this may not be possible due to congestion and capacity constraints. Without loss of generality, we will label \( O_j \) in increasing order of \( v_j \), i.e. \( v_1 \leq v_2 \leq \cdots \leq v_{N_o} \).

Each SP \( P_i \) can control three parameters. First, it can set \( p_i \in [0, 1] \), the price per unit flight of flying with that SP. Second, it invests in infrastructure to determine \( \alpha_i \in [0, 1] \), the multiplicative constant of delay. Third, it defines an allocation mechanism \( \beta^i(\hat{x}_i, j) : \mathcal{O} \times \mathcal{P} \rightarrow [0, 1] \), which determines how much of a requested flight allocation the operator \( j \) gets based on the total number of flights requested \( \hat{x}_i \). We assume that \( \beta^i \) is public and known to all airspace participants.

\( O_j \) chooses how they partner with each SP \( i \) by determining a flight distribution \( f_j = (f_j^1, \ldots, f_j^{N_o}) \), where \( f_j^i \in [0, 1] \forall P_i \in \mathcal{P} \) represents the proportion of flights requested to \( P_i \), and \( \sum_{i \in \mathcal{P}} f_j^i \leq 1 \). In airspace operations, \( O_j \) will request that capacity for \( f_j^i \hat{q}_j \) flights be allocated by \( P_i \). The total flights requested to SP \( P_i \) is defined by \( \hat{x}_i \):

\[
\hat{x}_i = \sum_{O_j \in \mathcal{O}} f_j^i \hat{q}_j,
\]

which may exceed \( c_i \). To respect its capacity constraint, \( P_i \) defines a valid mechanism \( \beta^i \) to give each operator \( \beta^i(\hat{x}_i, j) f_j^i \hat{q}_j \) flight slots, which determines the total flights actually flown \( x_i \):

\[
x_i = \sum_{O_j \in \mathcal{O}} \beta^i(\hat{x}_i, j) f_j^i \hat{q}_j
\]

2) Delay model: The number of flights actually flown has an effect on delay in the airspace. We represent this as a quadratic delay cost function given by \( \alpha_i(x_i/c_i)^2 \).

3) Allocation mechanism: We assume that a valid mechanism \( \beta^i \) is defined such that that \( x_i \leq c_i \). We write \( \beta^i(x_i, j) \) as \( \beta^i(x_i) \) for simplicity when the identity of the operator is apparent. One example of \( \beta^i \) is a proportional allocation, that allocates a fraction of the flights requested across all operators if \( \hat{x}_i > c_i \):

\[
\beta^i(\hat{x}_i) = \begin{cases} 
1 & \text{if } \hat{x}_i \leq c_i \\
\frac{c_i}{\hat{x}_i} & \text{o.w.}
\end{cases}
\]

One could also consider a preferential \( \beta^i \) based on proportional factors that maximizes the flights given to a particular operator \( j^* \):

\[
\beta^i(\hat{x}_i, j) = \begin{cases} 
\min(1, \frac{c_i}{f_j^i \hat{q}_j}) & \text{if } j = j^* \\
1 & \text{if } \forall j \neq j^* \text{ and } \hat{x}_i \leq c_i \\
\frac{c_i}{\hat{x}_i} & \text{o.w.}
\end{cases}
\]

Based on the mechanism from every SP \( \beta^i \forall P_i \in \mathcal{P} \), operator \( O_j \) ultimately gets to fly \( q_j^i \) flights with \( P_i \), and receives a reward per unit flight \( \pi_i^j \) such that:

\[
q_j^i = \beta^i(\hat{x}_i, j) f_j^i \hat{q}_j
\]

\[
\pi_i^j = v_j - p_i - \alpha_i(x_i/c_i)^2
\]
In the above, \( \pi^j_1 \) is the value per unit flight minus the price paid to SP \( i \) and the delay costs incurred.

Operators receive a consumer surplus \( S_j = \sum_{i \in P} q^j_i \pi^j_1 \). We will represent total consumer surplus as \( S = \sum_{O_j \in O} S_j \).

Each SP earns a profit \( R_i = x_i p_i - k_{\text{infra}}(\alpha_i) - bc_i \), where the infrastructure cost \( k_{\text{infra}} \) is a monotonically decreasing function such that as \( \alpha_i \) increases, \( k_{\text{infra}}(\alpha_i) \) decreases. Total profit is defined as \( R = \sum_{P_i \in P} R_i \). In this work, we assume that \( k_{\text{infra}}(\alpha_i) = \frac{k_i}{\alpha_i} \).

Using the proposed model of airspace resources, we model the interaction between the airspace authority, SPs, and operators as follows:

1) The airspace authority grants the SPs \( P_i \in P \) capacities \( c_i \). Each SP pays \( bc_i \) for the capacity it receives.
2) SPs in \( P \) announce an allocation mechanism \( \beta^j(x_i, j) \). They also simultaneously set a price \( p_i \) and a loss factor \( \alpha_i \).
3) Operators in \( O \) simultaneously choose flight distributions \( f_j^i \). This determines \( x_i \) by Eqn. (2).
4) Based on \( x_i \), SPs assign flight allocations based on \( \beta^j(x_i, j) \), and SPs and operators receive their rewards \( R_i \) and \( S_j \).

See Fig. 1 for a visual description of the model. The structure of this game follows the model of a Stackelberg game, where agents make sequential decisions at each level; however, agents at the same level make simultaneous decisions. This game can be solved using backward induction, where the agents at a higher level take into account the responses of agents at lower levels to their actions. We aim to study the equilibrium behavior of this airspace system under different assumptions.

We can show that for a given set of parameters from SPs, \( p_i, \alpha_i, \forall i \in P \), there exists a unique equilibrium of flight distributions \( f_j^i \forall i \in P, j \in O \). For brevity we do not include a proof; it can be shown that the second derivative of flight distributions \( f_j^i \forall i \in P, j \in O \) is always negative. We additionally hypothesize that there is a unique equilibrium for SPs. This hypothesis is supported by experimental results that converge on a unique equilibrium for \( x_1 \), and random ordering of operators for iterated best response consistently yields the same result for smaller numbers of operators.

A. Experimental methodology

Unless otherwise stated, we assume that the airspace authority does not charge SPs, but instead only regulates capacity (i.e., \( b = 0 \)). We also assume that the desired number of flights \( \sum_{O_j \in O} \hat{q_j} = 1 \); in other words, delays may be incurred but all flights can be flown. Similarly, we assume \( \beta^j \) is based on the proportional \( \beta_j \) in Eqn. (3) when SPs are not operators, and preferential \( \beta_i \) in Eqn. (4) when an SP is also a fleet operator. Because demand does not not exceed capacity, \( \beta^i = 1 \). Future work will relax these assumptions, and test the effects of different levels of congestion.

We set \( N_o = 20 \) in the numerical experiments in this paper, representing scenarios in which there is sufficient competition on the fleet operator side. We assume that \( \hat{q_j} = \frac{1}{N_o} \forall j \in O \). We search for equilibria among operators through iterated best response, holding the actions \( f_j^i \) for \( j \in O, j \neq j^* \) constant while finding the \( f_j^* \) that maximizes \( S_j \).
We also have SPs optimizing for multiple parameters using the equilibria found by iterated best response as a submodule. To optimize these values, such as \(p_1, \alpha_1, f_{\text{non}}\) (see Sec. III-B), we use global heuristic solvers to find solutions. While these solutions are heuristic and have no guarantees of optimality, they avoid searching into suboptimal equilibria and help ensure that we get replicable results.

III. Monopolistic SP

In this section, we assume that there is only one SP with a monopoly on this section of airspace, \(P_{\text{non}}\) with \(c_{\text{non}} = 1\). We study the baseline scenario for one monopoly SP, then investigate when that monopoly SP is also an operator with an arbitrary valuation.

A. Maximization of revenue and consumer surplus

We first study SP profit and consumer surplus with respect to \(p_{\text{mon}}, \alpha_{\text{mon}}\). We follow the assumptions in II-A. We additionally assign all capacity to the monopoly SP \(c_{\text{mon}} = 1\). The results were compared for different values of \(k = [0.1, 0.05, 0.01, 0.005]\), to understand the effect of infrastructure cost sensitivity on SP behavior. We use iterated best response to find optimal operator choices \(f_j^0\) with respect to \(p_1, \alpha_1\), and do this for every combination of values of \(p_1, \alpha_1 \in [0.1, 1]\), with step size of 0.05. Results are presented in Fig. 2.

The change in \(k\) has a large effect on the shape of the profit curve for \(P_{\text{mon}}\) (Fig. 2, top left). For \(k = 0.1\), the effect \(\alpha_{\text{mon}}\) has on the profit is large, and the shape of the profit curve for \(P_{\text{mon}}\) follows \(k/\alpha_{\text{mon}}\). On the other hand, for \(k = 0.001\), the curve of \(P_{\text{mon}}\) is affected more by the price \(p_{\text{mon}}\), which is optimal around 0.55 for all values of \(k\) tested. This price point balances the SP’s profit per operator with the number of operators that fly with it.

Consumer surplus \(S\) is plotted in Fig. 2 (top right). The consumer surplus is the same over all \(k\), because \(S\) only depends directly on \(\alpha_{\text{mon}}\) and \(p_{\text{mon}}\). The consumer has the most surplus when it has the best service for the lowest price, and we see that reflected in the plot at the lower left corner of the plot.

All profit curves, regardless of \(k\), converge on the optimal price \(p_{\text{mon}}^* \approx 0.55\) (the approximation is due to small differences from different \(c_{\text{mon}}\)). We thus further investigate the effect of \(k\) by taking a cross-section of the profit at \(p_{\text{mon}}^* = 0.55\). This shows that as \(k\) decreases, \(\alpha^*_{\text{mon}}\) increases, as it gets less expensive for the SP to lower delay (Fig. 2, bottom left).

In Fig. 2 (bottom right), we see how each operator responds to the \(p_{\text{mon}}, \alpha_{\text{mon}}\) set by \(P_{\text{mon}}\). Because \(\bar{q}_j = 1\), there are no cutoff effects from congestion and \(\hat{x}_{\text{non}} = x_{\text{non}}\). Thus, if the reward per flight for an operator \(\pi_j > 0\), the operator will try to operate as many flights as possible, until \(x\) reaches a point where \(\hat{q}_{\text{mon}}\pi_j\) reaches a maximum. This happens at a threshold operator, which will have a flight distribution somewhere between 0 and 1. When \(k\) is lower, it is cheaper for the SP to have a lower \(\alpha_{\text{mon}}\) and lower delay costs, which means that operators with lower valuation \(v_j\) can fly flights.

B. Monopolistic SP as a fleet operator

Now we assume that \(P_{\text{mon}}\) is also an operator \(O_{\text{mon}}\). The SP not only receives \(R_{\text{mon}}\), but also gets surplus \(S_{\text{mon}}\). Because of this, the flights that \(O_{\text{mon}}\) operates in partnership with \(P_{\text{mon}}\) do not need to pay the price \(p_{\text{mon}}\). Additionally, if \(P_{\text{mon}}\) is allowed to use preferential allocations \(\beta_{\text{mon}}(x_{\text{non}}, j)\), it can assign \(O_{\text{mon}}\) a preferential amount of capacity that increases \(S_{\text{mon}}\). Preferential allocations may become much more important when \(\sum \hat{q} \geq \epsilon_{\text{mon}}\), which we leave for analysis in future work.

For every operator in \(O\), we set \(O_{\text{mon}} = O_j\), and set \(v_{\text{mon}}\) to the replaced operator’s value \(v_j\). For each \(v_{\text{mon}}\), we have \(P_{\text{mon}}\) optimize its price and delay factor \(p_{\text{mon}}, \alpha_{\text{mon}}\) and the flight distribution \(f_{\text{mon}}\) for \(O_{\text{mon}}\), using a global heuristic optimizer. The inner loop involved all operators \(O_j \in O\) optimizing their flight distributions in response to \(p_{\text{mon}}, \alpha_{\text{mon}}, f_{\text{mon}}\), using iterated best response. The results are presented in Fig. 3.

Similarly to Fig. 2, as \(k\) decreases the flight distribution increases at smaller values \(v_{\text{mon}}\). However, the increases in \(f_{\text{mon}}\) occur much earlier than expected from just the effect of \(k\). This is because the monopoly SP does not charge \(p_{\text{mon}}\) to the monopoly operator, allowing the monopoly operator to increase \(f_{\text{mon}}\) much earlier, when \(v_j \geq \alpha_{\text{mon}}\left(\frac{x_{\text{non}}}{\hat{x}_{\text{mon}}}ight)^{\frac{1}{2}}\). In other words, if \(v_{\text{mon}}\) is relatively small, the SP retains capacity for other flights; as \(v_{\text{mon}}\) gets higher, the SP prioritizes its own traffic more.

\(p_{\text{mon}}\) and \(\alpha_{\text{mon}}\) do not vary dramatically for the SP at each value of \(k\). Because the SP’s operator \(O_{\text{mon}}\) is a small fraction of the total number of flights available, the altered decision-making by replacing \(O_j\) with \(O_{\text{mon}}\) has little effect. Future work will study if there are large changes to \(p_{\text{mon}}\) and \(\alpha_{\text{mon}}\) if \(\hat{q}_{\text{mon}}\) was significantly larger than other \(\hat{q}_j\).

IV. Multiple Competing SPs

Proposed AAM concepts of operations state that multiple SPs will be able to operate in the same region of airspace [1]. In this section, we investigate the effects of competition by having 2 SPs \(P_1, P_2\) that operators can contract with. SPs must reason about their pricing and delay, so as to maximize the number of operators choosing their services while also generating profits. We first study the effect of competition on profit, consumer surplus, and flight distributions of operators for two private SPs and one public and one private SP, then analyze when one of the SPs is also an operator.

A. Competitive private SPs

We study competition by simulating two competing, private SPs for \(k = 0.01\). We hold \(p_1 = 0.5, \alpha_1 = 0.5\) constant, and solve for operator equilibrium flight distributions \(f_1^1, f_2^1\) for all values \(p_2, \alpha_2 \in [0.1, 1]\), similar to Sec. III. We test with \(c_1 = 0.7\) and
c₁ = 0.3. Operator equilibrium was solved using iterated best response. The results can be seen in Fig. 4.

In the first column, we plot the profit $R_1, R_2$ for each SP. The flat sections of the the contour reflect areas where increases or changes in $p_2, \alpha_2$ do not change the flight distributions of operators. For example, the flat section towards the right for the plot when $c_1 = 0.7$ reflects that when $p_2$ increases beyond a certain threshold, for $p_1$ being held constant, $P_2$ gets no demand for flights. In both capacity scenarios, the best response of $P_2$ to the fixed $P_1$ occurs at a $p_2, \alpha_2$ where both SPs earn a positive profit. However, the SP with the large capacity earns the greater share of profit.

The second column shows the total consumer surplus under different conditions. When $c_1$ is smaller (the bottom row), the
effect of $p_2$ and $\alpha_2$ is larger, as indicated by the lowest and highest value for the case when $c_1 = 0.3$.

The third and fourth columns show the flight distributions $f_j^1, f_j^2$ for selected operators. Higher value operators are represented with darker surfaces and tend towards higher flight distributions, while lower value operators represented with lighter colors might not operate flights (e.g., $O_{20}$ often is the flat base of these plots). These plots show the impact of congestion on decision-making by operators. For example, in the top row, $f_{20}^1$ and $f_{15}^1$ are very similar when $p_2 > 0.3$ and $\alpha_2 > 0.3$. As $p_2$ and $\alpha_2$ decrease, both $O_{20}$ and $O_{15}$ move from partnering with $P_1$ to $P_2$. However, as $p_2$ and $\alpha_2$ become very small, the increase in $x_2$ and thus delay for SP 2 is such that $O_{20}$ finds it more profitable to switch back to $P_1$, while $O_{15}$ continues decreasing its partnership with $P_1$. In contrast, when $c_1 = 0.3$, there is a broad change in demand from $P_1$ to $P_2$, likely because the demand quickly reaches the capacity for $P_1$ and when $p_2, \alpha_2$ are both low $P_2$ still has less delay than $P_1$. The effect of $\alpha_2$ is relatively small on operators, because the flight distributions have little change with respect to $\alpha_2$. Lower value operators show a greater sensitivity to changes to $\alpha_2$.

**B. Public option SP**

While the proposed concepts of operations describe third-party service providers, the possibility of a public sector SP (i.e., a public option) has also been mentioned [2]. The existence of such a public option would serve as a counterbalance to private SPs taking advantage of monopoly positions, neutrally serve all operators without charging for services, and widen access to a greater base of users. In the Internet domain, public option (sometimes called municipal) ISPs have been studied and mentioned as a possible solution for net neutrality problems [16] [17].

We explore the existence of a public SP $P_{pub}$ in the AAM context that sets parameters $p_{pub} = 0, \alpha_{pub} = 1$. This would be a barebones SP that does not charge operators, and covers infrastructure costs with a nonzero $b$ value. We study its effects when it operates in the same airspace as a private SP. We follow the experimental procedure from Sec. IV-A and present the results in Fig. 5.

The operation of the public SP occurs at a very slight loss in the first column, because $p_{pub} = 0$. This slight loss can be compensated by charging for the capacity granted to private SPs, $b > 0$, which is possible if the private SP makes a positive profit. $P_2$ is quite limited in the profit it can earn when $c_{pub} = 0.7$, because it must set $p_2, \alpha_2$ at low values to compete with the free (though delayed) services of the public SP. However, when $c_{pub} = 0.3$, $R_2$ does not change significantly from the comparable example in the bottom left of Fig. 4.

Consumer surplus is greater than when there are two private
SPs, because $p_{pub} = 0$ and $P_2$ must compete with $P_{pub}$. Operators that wouldn’t operate many flights with private SPs are able to operate a small number of flights in partnership with the public SP, as seen in the third column. Many more flights choose the public operator for a larger parameter space of $p_2, \alpha_2$, using its free services as an alternative to the private SP. While higher valuation operators move towards the private SP as price go down, this actually frees up some space for other lower valuation operators to partner with the public SP instead.

Fig. 5 implies that a public SP can be a minority operator, at a small cost to the private SP, while still improving consumer surplus. Future work on this topic would relax several simplifying assumptions (e.g., $P_{q} = c$) and further model the outcomes arising from the existence of a public option SP.

C. SP as an Operator

In this section, we study when one of the SPs is also an operator. We find a point $p_1, p_2, \alpha_1, \alpha_2$ close to the equilibria between the two private SPs, and hold those parameters constant, given fixed $c_1, c_2$. We make the assumption that the SP parameters remain constant because Fig. 3 from Sec. III-B showed that these parameters do not shift significantly, and we follow the same argument that when $q_j$ is small it does not affect the strategy of SPs. We additionally make this assumption so as to keep the problem computationally tractable.

To find the equilibrium point, we set $c_1 = 0.7, k = 0.01$ and found $R_1, R_2$ for $p_1, \alpha_1, p_2, \alpha_2 \in [0.1, 1.0]$ with step size 0.1. We then further refined measurements around the best point with step size 0.01. We fixed our equilibrium, and replaced each $O_j$ with $O_P$ and set $v_P = v_j$. The optimization for $f_P$ was done using a heuristic differential evolution method; the optimization for other operators $f_j, \forall j \in O \{O_P\}$ was done using iterated best response. Both $P_1$ and $P_2$ were tested as the SP with operations, and different results were obtained because the two SPs have different capacities. These results are presented in Fig. 6.

Perturbations in the equilibrium solutions can be attributed to the use of a global heuristic solver and the possibility of multiple equilibria in the discrete case. However, it is clear that the SP optimizes its operator’s flight distribution to only use itself in both cases, and increases $f_P$ earlier than if that operator was not working with the SP. This is likely due to the waiving of payment by each SP. Additionally, SP 1 increases $f_P$ for lower values of $v_P$, likely because its increased capacity means lower delay costs. SP 2 instead focuses on supporting other operators with its limited capacity, and waits until $v_P$ is higher to act.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we characterized the behavior of third-party SPs in the AAM context, and proposed a three-tier model that
represented interactions between the airspace authority, SPs, and AAM operators. We used the model study the economic effects of inter-SP competition, and settings in which an SP also acts as an operator. We highlight two key conclusions of our analysis:

1) Allowing SPs to also be operators does not appear to have significant adverse effects on the system for low or moderate levels of congestion. However, this behavior may not hold when the demand becomes so high that flights need to be turned away due to a lack of capacity, rather than just incurring a delay cost.

2) Public option SPs can contribute to consumer surplus without major costs. A public option SP provides access to lower valuation operators, while still allowing private SPs to earn profits, a portion of which could be used to support the public SP.

Future work on the theoretical front includes formal proofs of existence of a unique equilibrium, which would further validate the empirical results presented in this paper. Additionally, some of the simplifying assumptions made so far could be relaxed to improve the generalizability of the models. For example, high levels of congestion could be modeled by increasing \( q_j \) such that \( x_i > c_i \) for large portions of the action space of \( p_i, \alpha_i \). Finally, interventions by the airspace authority that allow non-zero public SP costs (i.e., \( b > 0 \)) and even the imposition of constraints on \( c_i \) could help develop other forms of regulatory policy.

REFERENCES


Figure 6: Private SPs as operators, for two SPs, with SP parameters fixed at \( p_1 = 0.41, \alpha_1 = 0.25, p_2 = 0.32, \alpha_2 = 0.46 \).