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# A grid-based evolutionary spatial algorithm for airline service design in multi-airport systems

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## Abstract

This paper proposes an integrated modeling framework to support airline frequency planning in a multi-airport system. First, a grid-based spatial model is developed to estimate passenger demand as a function of air-service characteristics (such as flight frequency and airfare) and ground accessibility. Second, an evolutionary algorithm is proposed to provide decision support for the allocation of flights to airports belonging to the multi-airport system, subject to fleet availability, flow balance and operational requirements. We apply the proposed approach to model frequent flyer passengers departing from one of the major multi-airport systems in Europe. Our results show that the degree of diversification of a multi-airport system—i.e., the presence of alternative airports—plays a significant role on both the demand and supply sides, providing passengers with more diversified and accessible services and providing airlines with higher operational flexibility and resilience in case of disruptions. Our modeling framework can be extended to capture additional managerial objectives or practical requirements.

*Keywords:* Multi-airport systems, air travel demand, frequency planning, genetic algorithm, frequent flyer passengers

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## 1. Introduction

The continuous growth of air transport and the shortage of capacity have made multi-airport systems (MAS) important mechanisms to meet demand in large metropolitan areas. In a multi-airport system, different airports are leveraged to serve the same (or part of the same) catchment area, instead of enlarging capacity at only one site. As a result, air transport supply distributes across different airports, and so are passenger flows. From a supply perspective, the presence of multiple airports leads to duplication of infrastructures. On the one hand, this limits the benefits of economies of scale, while it contributes to reduce airport congestion. Further, the presence of alternative airports may foster ac-

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cessibility to air transport services and enable differentiation strategies at both airport and airline level (de Neufville, 1995).

Over the last decades, the literature has investigated multi-airport systems from different standpoints, from the analysis of passenger allocation based on airport-airline-access choice modeling (e.g., Pels et al., 2000, 2001, 2003; Başar and Bhat, 2004; Hess and Polak, 2005, 2006; Ishii et al., 2009; Marcucci and Gatta, 2011), to the optimization of MAS operations (Sidiropoulos et al., 2018), encompassing the utilization of runways and airspace and the efficient planning of arrival-departure capacity trade-offs (e.g., Ramanujam and Balakrishnan, 2009; Murça and Hansman, 2018; Carmona et al., 2020; Schefers et al., 2020). By contrast, studies focusing on airlines' service planning in a MAS have been fairly scant and so are decision support tools to practically support airlines in this task. A key issue of airline planning in a multi-airport system is the decisions concerning whether (and how) to diversify services across airports, or rather concentrating them into a single airport. Allocating flights to different airports in the same MAS can be desirable for a number of reasons; from a supply perspective, it may be driven by capacity considerations, such as slot constraints, and serve as a risk mitigation strategy; from the demand perspective, pursuing a multi-airport supply strategy allows to exploit airport specificities to provide diversified services and potentially improve accessibility to passengers.

In addressing this topic, we propose an integrated modeling framework to support airlines in carrying out frequency planning activities in a MAS, that is, to determine how many and how to distribute flights across time and airports. First, we develop a grid-based demand model. Relying on proprietary data featuring the exact origin location of historical passenger trips, we estimate the number of passengers travelling from each spatial grid cell in a given time-window as a function of airline services and airport ground accessibility. Second, we develop and apply an evolutionary algorithm to solve the airline frequency planning problem in a MAS that integrates our grid-based demand model and eventually identifies the best MAS supply configurations. We apply the modeling framework to a large multi-airport systems in Europe. We consider a business route historically operated by a national flag carrier under a semi-monopolistic market structure and focus on the key and most strategic passenger segment on the route, i.e., corporate frequent-flyer passengers.

The remainder of this work is organized as follows. Section 2 describes our modeling framework. Section 3 presents the demand model, and Section 4 illustrates the development of the evolutionary algorithm, whose application is presented in Section 5. Conclusions and future research directions are outlined in Section 6.

## 2. Modeling framework

In this section, we present the main modeling elements and notation. We consider one of the largest multi-airport systems in Europe, where three airports ($\mathcal{A} = \{A, B, C\}$) coexist in serving a densely populated metropolitan area [1]. We focus on a relevant domestic route operated by a legacy carrier from the three MAS airports to a unique destination ($D$), under a "semi-monopolistic" regime [2]. We note that this empirical setting represents an interesting case study to investigate the effects of MAS supply diversification, for two main reasons. First, the services provided by the carrier in the MAS has effectively changed in the period under consideration (2017-2019) with significant variations in the use of different airports. Second, narrowing down the investigation to a monopolistic route allows us to focus explicitly on the impact of service diversification on passenger demand.

We identify the originating catchment area considering a fixed *"as the crow flies"* radius of 150 km around the metropolitan centroid, evenly divided into rectangular grid cells of $15km^2$ (See Figure 1). Passenger demand is defined for each grid cell as the sum of originating (or destining) trips. We further segment passenger demand across travel periods by considering 3-hour time windows, i.e., 6:00-9:00 am, 9:00-12:00 pm, 12:00-3:00 pm, etc. Ultimately, demand trips are characterized by their trip direction, either outbound *($A,B,C$ to $D$)* or inbound *($D$ to $A,B,C$)*.

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[1] Carrier's and data features' identification are suppressed in the paper due to data disclosure policies.

[2] The target airline has operated the large majority of the services in the studied market, whereas competing airlines have provided only sporadic and discontinuous services to passengers, thus not constituting a realistic threat. This is especially true for the segment of passengers considered in this study, i.e., frequent flyer, which is characterized by a high level of loyalty compared to other passenger types (Agostini et al., 2015). The route has been further affected by intermodal competition exerted by rail services. However, the provision of rail services on the designated route has been fairly constant along the period considered and thus implicitly captured by means of fixed effects in the panel demand model (See Section 3).

Let us denote the set of grid cells as $\mathcal{I}$ (indexed by $i$), the set of time windows as $\mathcal{W}$ (indexed by $w$), the set of months as $\mathcal{T}$ (indexed by $t$) and the set of directions as $\mathcal{R}$ (indexed by $r$). We thus define our passenger demand observations as $D_{iwrt}$.

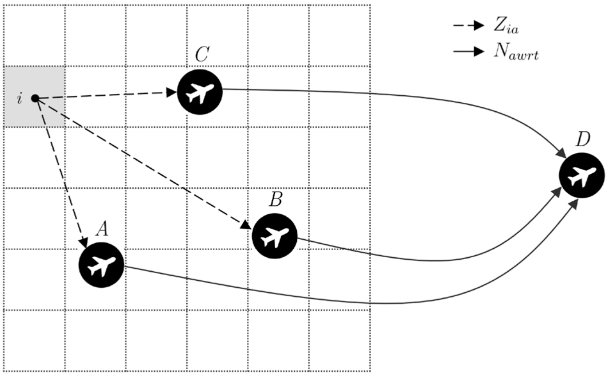

Fig. 1: Illustration of a prototype multi airport system

## 3. Demand model

### 3.1. Model Formulation

Grounding on previous studies (e.g., Birolini et al., 2021; Ishii et al., 2009), we model passenger demand from/to each grid cell in a given time window as a function of three main determinants, i.e., ground accessibility (proxied by the access cost), frequency and price of airline services. In detail, our model specification is as follows:

$$\ln(D_{iwrt}) = \beta_1 \ln(N_{wrt}) + \beta_2 P_{wrt} + \beta_3 Z_{iwrt} + \beta_4 MAS_{wt} + \psi_{wt} + \theta_{iw} + \gamma_t \quad (1)$$

where $N_{wrt}$ is the total number of flights provided by the carrier (from any airport in the MAS, i.e., $N_{wrt} = \sum_{a\in\mathcal{A}} N_{awrt}$) and $P_{wrt}$ is the average ticket price[3]. We then consider an aggregate ground access cost index ($Z_{iwrt}$) that quantifies the ease to access the airport system from each grid cell. We computed this index as follows: $Z_{iwrt} = \sum_{a\in\mathcal{A}} Z_{ia}(N_{wart}/N_{wrt})$, where the cost of accessing any airport $a$ from grid cell $i$ ($Z_{ia}$) is weighted by the portion of flight supply at airport $a$. Similar to Birolini et al. (2019), access costs were collected from Google Maps and ViaMichelin and refer to the private mode (i.e., driving a car).

We further consider two features to characterize the structure and operations of the multi-airport system. First, we consider the number of airports served by the carrier ($MAS_{wt}$), leading to a single-, two-, or three airport structure. Second, we include a set of airport specific effects ($\psi_{wt}$) to capture additional features that are not directly captured by other regressors, such as the presence of accessible parking spaces, transit frequencies to and from the terminal, and lounge services, as important facilities that impact airport attractiveness, especially for frequency flyers. Eventually, the inclusion of monthly fixed effects contributes to capture time trends and seasonality patterns ($\gamma_t$), while grid-time window fixed effects capture the intrinsic average propensity to fly of passengers in a givenn cell $i$ at time period $w$ ($\theta_{iw}$).

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[3] Note that frequency and price variables are defined at an aggregate carrier-level (invariant across grid cells), while passenger demand is defined at a grid level. In turn, this reduces issues of reciprocal causality.

### *3.2. Results*

The demand model outlined in Equation 1 is estimated using a fixed-effects Poisson panel model. Despite the total number of passengers traveling from each grid is a non-negative count variable with over-dispersion (Hausman and McFadden, 1984)—while a Poisson model assumes equi-dispersion—-using a Poisson model has several desirable properties that makes it the most robust approach also in the case of over-dispersed data (Wooldridge, 1999).

Table 1: Demand estimates of frequent-flyer passengers with 3-hour time windows.

| Variable | FE Poisson panel | | FE Negative Binomial panel | |
|---|---|---|---|---|
| | *(1) Outbound* | *(2) Inbound* | *(3) Outbound* | *(4) Inbound* |
| ln(frequency) | $0.1522^{***}$ | $0.3711^{***}$ | $0.2957^{***}$ | $0.4675^{***}$ |
| | (0.0193) | (0.0353) | (0.0322) | (0.0489) |
| Fares | $-0.0027^{***}$ | $-0.0012^{**}$ | 0.0002 | -0.001 |
| | (0.0005) | (0.0006) | (0.0009) | (0.0009) |
| Access cost | $-0.0267^{***}$ | | $-0.0319^{***}$ | |
| | (0.0086) | | (0.0094) | |
| Egress cost | | $-0.0719^{**}$ | | $-0.0518^{***}$ |
| | | (0.0285) | | (0.0092) |
| MAS: Two-airports | $0.8756^{***}$ | $1.1413^{***}$ | $0.8749^{***}$ | $1.0124^{***}$ |
| | (0.0241) | (0.0261) | (0.0425) | (0.0407) |
| MAS: Three-airports | $0.2218^{***}$ | $0.6841^{***}$ | $0.4566^{***}$ | $0.6726^{***}$ |
| | (0.0507) | (0.0527) | (0.08) | (0.0789) |
| Constant | | | $-1.2305^{***}$ | $-1.4727^{***}$ |
| | | | (0.2449) | (0.282) |
| Airport-fixed effects | *YES* | *YES* | *YES* | *YES* |
| Month-fixed effects | *YES* | *YES* | *YES* | *YES* |
| Grid-time window fixed effects | *YES* | *YES* | *YES* | *YES* |
| Observations | 23103 | 23960 | 23103 | 23960 |
| Number of groups | 931 | 966 | 931 | 966 |

Results are summarized in Table 1. Models 1 and 2 report the results of the fixed-effects Poisson panel model related to outbound and inbound flows, respectively. Coefficients are statistically significant and their signs are consistent with expectations. An increase in the number of flights is positively correlated to passenger flows and airfare is found to have a significant negative impact. Our results also highlight that corporate frequent flyer passengers are highly sensitive to access/egress costs. Their business attitude discourages them to travel longer distances to access (or egress) the airport.

Most importantly, results highlight that two- and three-airport structures are preferred over the reference single-airport case, thus suggesting that diversifying the flight supply across neighboring airports positively affects passenger demand. However, a two-airport configuration seems to be preferred to a three-airport one. In turn, this highlights a trade-off between service diversification and inefficiencies associated with the decoupling of activities at different airports. The spread of operations across too many airports may indeed lead to the detriment of service effectiveness and low frequencies (at the expenses of higher schedule delays at each airport).

Ultimately, Models 3 and 4 (Table 1) present the econometric results obtained by using a fixed effects Negative binomial panel model. Overall, the small deviations in the estimates corroborate our results.

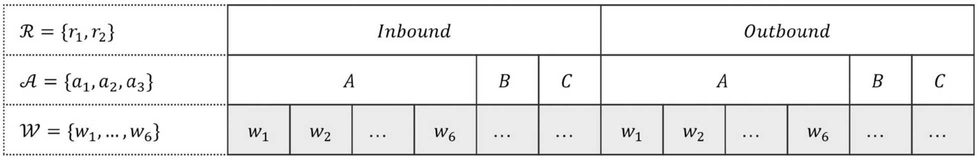
## 4. Evolutionary algorithm

To illustrate the applicability and the benefits that can be derived by the application of our grid-based spatial demand model, we consider in this section an airline optimization model that maximizes the number of passengers by deciding the number of flights to be provided at the different MAS airports (across time windows, directions and months, i.e., $N_{awrt}$), subject to fleet availability, flow balance, and operational constraints. The incorporation of our demand function (Equation 1) makes the original frequency planning problem a mixed-integer nonlinear model, which is very difficult to solve by exact methods. Therefore, we propose an ad-hoc heuristic evolutionary algorithm. Specifically, we formulate our algorithm as a genetic algorithm due to the structure of the problem and, in particular, the decision variables, which can be conveniently encoded into integer strings (i.e., chromosomes), as detailed in Section 4.1. According to the Darwinian principle of survival of the fittest, our algorithm starts from an initial population of randomly generated chromosomes and creates a new population that repeatedly evolves until high quality solutions are attained in a finite number of iterations. At each iteration, the algorithm updates the population of candidate solutions by means of genetic operators (such as selection and mutation) (e.g., Goldberg, 1989) that probabilistically combine and alter the existing individuals to obtain a new generation of individuals.

### 4.1. Encoding

Using the same notation given in Section 2 and considering a given month $t$ (omitted from now on), we now detail the main features of our evolutionary algorithm.

*Genes*—i.e., single elements of a chromosome—represent the number of flights allocated in a given time window ($w$), at a given airport ($a$), either inbound or outbound ($r$) (i.e., $N_{awr}$). A chromosome is thus constituted by an ordered array of $|W| * |A| * |R| = 6 * 3 * 2 = 36$ genes that represent a potential airline frequency configuration. An illustrative representation of the chromosome encoding is shown in Figure 2.



| $\mathcal{R} = \{r_1, r_2\}$ | *Inbound* | | | | | | *Outbound* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\mathcal{A} = \{a_1, a_2, a_3\}$ | *A* | | | | *B* | *C* | *A* | | | | *B* | *C* |
| $\mathcal{W} = \{w_1, \ldots, w_6\}$ | $w_1$ | $w_2$ | … | $w_6$ | … | … | $w_1$ | $w_2$ | … | $w_6$ | … | … |

Fig. 2: Graphical representation of a chromosome

*Fitness function*: At each iteration, each chromosome in the population is evaluated using a fitness function that assesses the performance of the chromosome. The fitness function can be synthetically expressed as:

$$\varphi = \sum_{i \in \mathcal{I}} \sum_{w \in \mathcal{W}} \sum_{r \in \mathcal{R}} D_{iwr}(N_{awr}) \tag{2}$$

where $\varphi$ stands for the sum of passengers over grid cells ($i$), time windows ($w$) and directions ($r$). Note that the frequencies represent the decision variables of our model, while the other factors included in the demand model (e.g., grid fixed effects, average fares, and access/egress costs, see Equation 1) act as parameters. Therefore, $D_{iwrt}$ is solely function of the frequency allocation represented by the variables $N_{awr}$.

*Constraints*: To retrieve feasible solutions, we apply a set of penalties to the fitness function to account for infeasibilities that may result from the recombination of genes carried out by genetic operators. Specifically, we penalize the fitness function to account for three main operational restrictions: 1) *Slot constraints*, enforced by counting the number of flights exceeding the maximum number of flights that the target airline can operate in each specific combination ($w$, $r$, $t$); 2) *Flow Balance*, that is, enforcing the same number of inbound and outbound flights at each airport; and 3) *Fleet utilization*, implemented by setting a cap on the maximum number of flights operated (computed from the current fleet and considering average utilization rates). Penalties to the fitness function are calculated as the sum of flights violating the abovementioned constraints, and converting it in the equivalent number of passengers—assuming average aircraft capacity and load factors.

### 4.2. Evolutionary strategy

*Population initialization procedure*: The first step of the genetic algorithm consists of generating an initial population of $N$ feasible solutions. Each new solution is created by applying a (positive or negative) random perturbation to the MAS supply configuration—i.e., an increase or a decrease to the number of flights. Specifically, we use the following approach:

1. Randomly choose (uniformly) an integer $\delta \in (0; \bar{\delta}]$ and a given airport $a_1 \in A$.
2. Modify inbound and outbound flights (genes) at airport $a_1$ applying a variation equal to $\delta$, which is then randomly distributed across time windows, such that $\sum_{w\in\mathcal{W}} N_{awr_{out}}=\delta$ and $\sum_{w\in\mathcal{W}} N_{awr_{in}}=\delta$.
3. Randomly identify two integers $\alpha$ and $\beta$ such that their sum compensates variation $\delta$, i.e., $\alpha+\beta=-\delta$.
4. Apply variations $\alpha$ and $\beta$ to airports $a_2$ and $a_3$, respectively, repeating step [2] for each airport.

*Selection (elitism)*: At each iteration the most well adapted individuals are selected in light of the *"survival of the fittest"* principle—those with the highest fitness value—and are directly transferred into the new population to drive the GA in reaching the global optimum. However, the tendency to directly transfer the best solutions into the new population might introduce selectivity pressure into the procedure preventing the algorithm to appropriately explore the solution space. Aimed at achieving a balance between premature convergence and genetic diversity we implemented a mixed selection operation as in Zhang et al. (2019), where the GA both reserves elite and poor individuals to pursue global optimization.

*Mutation*: After the *Selection* phase, the new population is completed including a further set of mutated chromosomes, generated as follows:

1. Choose a chromosome $c$ from the previous population generation using a fitness-proportional roulette wheel selection.
2. Apply a differential mutation operator to increase the diversity of potential solutions in the next iteration. This mutation operators recombines the genes in chromosome $c$ to form a new offspring by employing steps [1-4] of the *Population initialization procedure*.
3. Apply with probability $p$ an evolutionary mutation. This operator perturbates chromosome $c$ by applying steps [1-2] of the *population initialization procedure* to each airport belonging to the set $A$.

## 5. Illustrative example

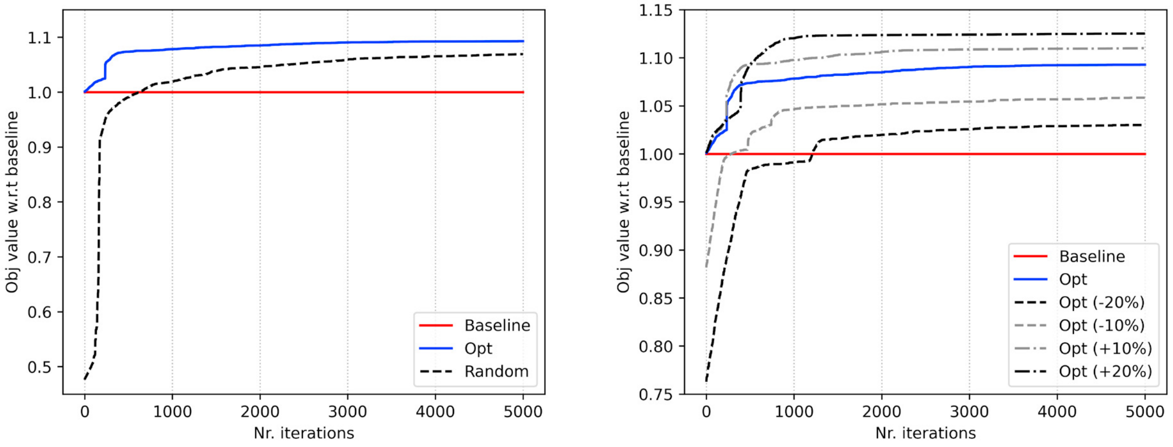
### 5.1. Experimental setup

In this section, we present the application of the proposed evolutionary algorithm to the empirical setting presented in Section 2. Overall, we consider 5 scenarios and a baseline scenario, corresponding to the current situation as of June 2018. Scenario 1 considers the same total number of flight threshold as in the baseline scenario, but optimizes the allocation of supply across the three airports; Scenario 2 and Scenario 3 simulates an increase in capacity by 10% and 20%, respectively; Scenario 4 and Scenario 5 introduce a more restrictive cap decreasing the maximum allowable number of flights by 10% and 20% relative to the baseline. Eventually, the analysis investigates the best supply configuration the airline should undertake in the case one of the three airports interrupts its activity.

We implemented our evolutionary algorithm considering the following fine-tuned parameters: population size = 300, number of generations = 5000, selection rate = 5%, evolution mutation rate = 7.5%, maximum mutation variation=5 flights. The procedure was implemented using Python 3.6, on an Intel(R) Core(TM) i7-8700K CPU with a frequency of 3.70 GHz and 32 GB of RAM.

### 5.2. Evolutionary algorithm results

We first test the validity of our *population initialization procedure* against a random initialization approach. Figure 3a shows that our approach provides higher quality initial solutions that can help the GA to converge toward high quality solutions faster. Experimental findings reveal that the optimal supply configuration identified by the proposed evolutionary algorithm at termination considerably outperforms the baseline case—i.e., demand estimates based on June 2018 data—by enhancing passenger demand by 9.3% (Opt vs. Baseline in Figure 3b). A deeper look into the results highlights that the improvement in the number of passengers is achieved by allocating more flights during the 3:00-6:00 pm time-window and by reducing frequency during 9:00-12:00 am and 6:00-10:00 pm. Our evolutionary procedure suggests to anticipate inbound flights during the afternoon time window as a valid alternative for corporate frequent-flyer passengers carrying out daily work commitments in the morning at the destination metropolitan city. This is proposed at the expenses of the already saturated on-peak time-window of the early evening (6:00-10:00 pm). Furthermore, the reduction of flights is also applied to the late morning time-window, which represents an off-peak window that generally does not suitably accommodate business passengers' time preferences.



(a) Initialization population procedure

(b) Comparison of optimization scenarios

Fig. 3: Evolutionary algorithm performance

Figure 3b illustrates the results obtained under each considered scenario. First, Scenarios 2 and 3 show that an increase in the total number of operated flights, by 10% and 20%, sets the conditions for an additional stimulation of passenger demand compared to Scenario 1's performance, by 1.6% and 3.0%, respectively. Flights are mostly allocated in correspondence with time-windows that remained relatively less saturated under Scenario 1. Second, Scenarios 4 and 5 apply a reduction to total frequency by 10% and 20%, respectively. Reductions lead to a drop in passenger demand equal to -3.1% and -5.7%, which mostly occur after midday. Regarding the evolutionary pattern of each scenario (see Figure 5), on average, all trends reach 99.8% of the maximum objective value after 1200 iterations and 162.2 minutes. Note that for our purposes computational time is not a concern as the presented approach is not aimed to provide an operational, day-ahead practical tool for flight allocation, but a decision support tool to airlines in carrying out strategic and tactical evaluations of frequency planning in a multi-airport system context.

Eventually, the model is used to evaluate the re-assignment of flights following the closure of one of the airports within the multi-airport system. Specifically, the closure of the most active airport in the system ($B$ in our case) would lead to an important decrease in the total number of flights offered by the airline (-85%). This decrease is however mitigated and reduces to -63% due to the shift of part of the airline's offer towards the other two airports—i.e., $A$ and $C$—, which would in turn provide 67% and 33% of the airlines' total offer, respectively. Overall, these results suggest that the presence of a more diversified supply that includes alternative active airports could increase the resilience of the multi-airport system reducing its vulnerability to disruptive events or maintenance closures (e.g., runway renovation).

## 6. Conclusion

In this paper we develop an integrated modeling framework that provides a decision support tool for airlines' frequency planning in a multi-airport system context. By leveraging on data featuring the spatial distribution of passengers relative to MAS airports and detailed information of their time-of-day of departure, we first elaborate a grid-based demand model to evaluate the impact of key air-service attributes, as frequency and fare, and MAS characteristics, meaning the access cost and the level of supply diversification. Second, we illustrate the practical validity of our approach integrating the demand model into an evolutionary algorithm aimed at optimally designing the airline supply configuration under operational considerations. Results provide evidence that the degree of diversification of a multi-airport system plays a significant role in determining passenger demand. The two-airport structure is found to be the preferred configuration, able to balance the advantages of having a denser service on the territory and the disadvantage of replicating the service in different nearby airports. The implementation of the proposed framework can be indeed informative for airline managers to set up strategic activities and face the increasing complexity that characterizes airlines' supply processes in multi-airport system contexts. Our grid-based model can be also noteworthy for airports' managers and policymakers as a valid framework to strategically identify suitable capacity configurations aimed at alleviating congestion problems and minimize the environmental impact. An accurate evaluation of differentiation strategies could indeed allow to preserve the regional benefits of an increasing demand while monitoring region's environmental issues, such as noise and air pollution.

In summary, to our knowledge, this study develops the first decision support tool for airline frequency planning in multi-airport systems. Future research can further extend the proposed modeling to more carefully appraise other operational aspects, as well as enable a profit maximising objective function and extend it to non-monopolistic routes.

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