

The Economic Value of Adding Capacity at Airports

A Data-driven Model

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Abstract—This article presents a model for the economic value of adding capacity at airports. We start with an extensive literature review, discussing the main findings covering costs and revenues at airports, in particular related to their capacity. We then proceed to an analysis based on a wide range of data sources (financial, operational, quality of service) which have been synthesised into one database. The analysis itself yields interesting results, such as the presence of distinct types of airport and their characteristics. Broadly based on the knowledge gained from the data analysis, we describe a functional model describing the costs and revenues associated with an increase of capacity at an airport. We show how the model can be calibrated with data and present some preliminary results based on the calibration of Paris Charles de Gaulle airport.

I. INTRODUCTION AND OBJECTIVES

This study contributes to SESAR Operational Focus Area 05.01.01 (Airport Operations Management) in relation to the development of the AirPort Operations Centre (APOC) concept. The objective of the study is to extrapolate to airports, the model currently used [1] for en-route capacity planning, as represented in Figure 1. This methodology, exploring the economic optimum (minimum total cost to the airspace users), when considering the balance between the cost of capacity provision and delay costs (due to lack of capacity), is now used extensively to allocate EU-wide delay targets to individual Functional Airspace Blocks and air navigation service providers (ANSPs). The study presented in this paper sought to similarly evaluate the optimum airport economic value based on several cost functions and a quality of service measure. We set out to explore whether it was possible to identify the optimum amount of additional capacity to add to an airport, beyond which diminished returns might be expected, driven by increased delays and reduced quality of service.

The project thus assesses the value of additional passengers, or additional capacity, at an airport. It aims to qualify and quantify the main relationships and trade-offs between variables such as capacity, profitability and quality of service. A novel feature is the assessment of passenger satisfaction data. The implementation follows a data-driven approach: modelling decisions are primarily supported by traffic, passen-

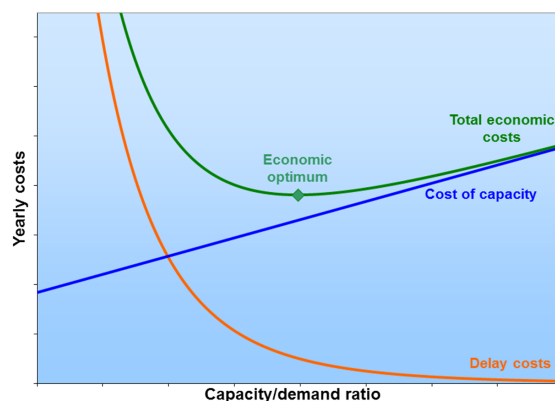


Figure 1. Economic cost optimum in en-route delay/capacity trade-off.

ger, economic and performance data analysis, encompassing data reduction techniques such as clustering and principal components analysis. This paper reports on the first results of this research. In Section 2, we review the state of the art in relation to the literature and data availability. In Section 3 we describe the principles of the modelling process. Section 4 illustrates progress towards the development of the generic model. Section 5 draws together early observations from the modelling, conclusions from the work completed to date, and discusses the next steps and key development opportunities foreseen.

II. STATE OF THE ART

A. Literature review

This review provides a summary of the key relationships between variables influencing the airport economic value, and the mechanisms for dealing with airport capacity issues, as reported in the research literature. Excess airport capacity will create minimal delays but will be unprofitable for airports, who will be incentivised to utilise their facilities as much as they can, since a significant proportion of their operating costs are fixed [2]. Excess demand will produce delay costs

for airlines and passengers [3]. The delays will mean that passengers spend longer at the airport and make more use of commercial facilities, which has been viewed as a positive externality of congestion [4], even though the only empirical study found directly in this area has found no significant relationship between commercial revenues and delayed flights [5]. Airport passenger satisfaction, likely to drop with delays, has also been seen to be positively associated with commercial spend [6]. The resulting relationship between satisfaction and profitability has not always been confirmed [7], but research here is very scarce because of the lack of appropriate and publicly available satisfaction data.

In trying to match more closely demand and capacity, the literature discusses two main options for airports. First, there are so-called ‘soft’ management approaches, that tend to be quick to implement, potentially low cost, but limited in scope as they do not involve any major changes to the physical infrastructure. ‘Hard’ options, by contrast, are slow to implement and expensive. These can yield large increases in capacity, because they are lumpy and are made infrequently in relatively large indivisible units. These two approaches are simultaneously considered by airports, and lead to a two stage optimisation, as shown in [8], with different time frames.

The soft options can relate to both strategic planning and tactical adjustments [9]. In the broadest sense, these can include substituting short-distance air travel with high-speed trains, diverting traffic to other airports or using multi-airport systems [10]. For the airport itself, options may be infrastructure improvement planning [11] [12], changing the ATC rules, reorganising traffic to make better off-peak use of facilities, or by using aircraft with higher seat capacity, even though it is argued this may lead to additional congestion in the terminals [13] [14].

A major consideration is whether congestion or peak pricing can be used to manage demand. The theoretical issues have been discussed in depth [15] but rarely has this been implemented in practice. Research has also shown that business passengers, exhibiting a high value of time, would benefit from increased charges to protect them from excessive congestion caused by leisure passengers with a lower relative time value [16] [17]. However, in the short-term, any changes in prices may not be possible if the airport is subject to economic regulation, especially price-cap regulation which is a common situation [18]. An alternative demand management technique, frequently researched and independent of the economic regulation mechanism, is a reformed slot allocation process, probably using slot auctions or trading systems, which would have major financial consequences for airlines and passengers, but less certain impacts on airport revenues [19] [20].

In discussing the provision of hard infrastructure, it has been argued that the uncertainty of future demand [8] and the unpredictability of capacity degradation should be considered [21]. Increasing capacity locally can have major unforeseen wider impacts, for example, because of the network effects of delays [3]. Trade-offs between different types of providing capacity at departure and capacity at arrival have been identified [22]

and the relationship between runway and terminal capacity examined [23] [24]. It is contended that runway capacity should be prioritised since this is what causes bottlenecks for most airports [13] [14]. There is also the trade-off between focusing on operational and commercial capacity, the extent of complementarity between these two different areas, and the associated cost allocation approaches [25] [4]. This links to another important issue, explored in some depth in the literature, related to airport incentives to invest, particularly if they are subject to economic regulation [26].

Previous research has identified some of the cost and revenue implications for airports if they opt for hard infrastructure, grow in size and maybe evolve into a new type of airport with different operations and/or traffic mix. Larger airports are generally able to provide a greater range of commercial facilities, thus increasing the commercial spend, whilst leisure passengers have been shown to spend more than business passengers [5] [27], and low cost carrier (LCC) passengers less [28]. Traffic mix changes will also bring associated costs, related to the service expectations of the airlines, such as ensuring a fast transfer time for hub airports, or swift turnarounds for LCCs. As regards airport size, evidence is mixed but generally it shows that airports experience economies of scale, albeit with different findings related to if, and when, these are exhausted and if diseconomies then occur [29] [30].

The costs of any additional capacity will be reflected in increased airport charges, but aeronautical revenues have also been found to be strongly influenced by market-oriented factors, such as price sensitivity and competition [31] [32]. The potential impact of price changes appears quite limited, as they represent quite a small share of airline costs, but it has been argued that the actual effects will depend on whether the increases are passed on fully to passengers, and the supply side responses by airlines, and consequently may actually result in a much wider impact [33], although this is difficult to support with empirical research.

This brief literature review has identified many of the key potential trade-offs relevant to this research. It has also enabled an assessment to be made of the main variables used, for example related to aircraft movements, passengers, airport characteristics and capacities, which has informed our own choice of parameters. This now leads on to the consideration of data availability.

B. Data availability

The reference year for the analyses is 2014, this being the most recent year for which the data required were most generally available. From multiple sources, a consolidated database was compiled. A major component of this was airport financial and operational data sourced (through subscription) from FlightGlobal (London, UK). ATRS (Air Transport Research Society; USA and Canada) benchmarking study data were purchased, in addition, particularly for the provision of complementary data on airports’ costs and incomes. At the time of analyses, only ATRS data for 2013 were available, and these selected data were used as a proxy for 2014. Financial

and operational data were compared with in-house, proprietary databases, with adjustments made as necessary. Data on airport ownership, and additional data on passenger numbers, were provided by Airports Council International (ACI) EUROPE (Brussels). European traffic data were sourced from EUROCONTROL's Demand Data Repository (DDR) with delay data primarily from the Central Office for Delays Analysis (EUROCONTROL, Brussels). Note that, importantly, local turnaround delay is used throughout this paper, as this reflects airport *in situ* effects, whereas air traffic flow management departure delay is generated due to en-route delay, or delay at the destination airport - i.e. it is attributable to remote effects. We did not have access to clean, local (airport generated) air navigation service (ANS) delay data. Other in-house sources of data were used in addition to those listed, also drawing on the literature review, above.

In the absence of access to a single, comprehensive source of passenger quality of service data, airports were assigned an overall passenger satisfaction ranking for 2014, initially based on Skytrax "The World's Top 100 Airports in 2014" ranking data¹, and then adjusted according to independent reviews by two experts, in addition to some limited inputs from ACI (Montreal, Canada) drawing on its Airport Service Quality [6] programme data. On this basis, the airports were allocated to a 'top', 'middle' or 'lower' ranking. (Notwithstanding fairly extensive industrial action in 2014², clearly impacting a number of passengers at specific airports, it is difficult to assess the collateral (confounding) impact of such events on corresponding passenger satisfaction scores for such airports.) The final rankings derived cannot be shown due to confidentiality restrictions. This new parameter derived by the team is one of many important inputs informing the cluster analysis of III-B. To our knowledge, this is the first time that such a very wide range of data has been synthesised in one database and used to characterise airport performance.

III. DATA ANALYSIS

In this section we explore the data collected, in order to draw some high-level conclusions. These analyses were undertaken in order to drive the modelling process, but they are severally valuable in their own right, we suggest, bearing in mind the unique consolidation of data sources achieved.

A. High-level results and PCA

1) *Correlation structure*: We begin by selecting the type of data that should, at least in theory, be included in the model or could influence the modelling process. Table I shows the variables we selected, with a simple description for each of them. We define the net basic utility as the financial operating result of the airport minus the cost of the (local, turnaround) delay.

¹http://www.worldairportawards.com/Awards/world_airport_rating_2014.html

²Air traffic control - Belgium: June, December; France: January, March, May, June; Greece: November; Italy: December. Airlines - Air France: September; Germanwings: April, August, October; Lufthansa: April, September, October, December; TAP Air Portugal: December.

TABLE I
METRICS USED TO CHARACTERISE THE AIRPORTS.

Abbreviation	Short description
AO_tot	Number of airlines
CUI	Capacity utilization index
NBU	Net basic utility
cap	Runway hourly capacity
cht	Share of low-cost companies
fsc	Share of traditional carriers
delay_per_flight	Delay per flight
delay_tot	Cumulative turnaround delay
exp_tot	Total yearly expenses
flight_EU	Share of European flights
flight_per_rnwy	Flights per runway
flight_per_term	Flights per terminal
flight_tot	Total number of flights
gate_tot	Number of gates
term_tot	Number of terminals
pax_per_flight	Passengers per flight
pax_tot	Number of passengers
rev_areo	Aeronautical revenues
rev_non_area	Non-aeronautical revenues
rnwy_tot	Number of runways
route_tot	Number of routes
sat	Passenger satisfaction

The data in Table II shows statistical associations recently reported by Airports Council International in a report [6] exploring, *inter alia*, whether passenger satisfaction increases airport non-aeronautical revenues. The value corresponding to the global passenger satisfaction mean relates to ACI's Airport Service Quality (ASQ) programme - the associated 1.5 per cent growth in non-aeronautical revenue being an average increase.

TABLE II
ACI REPORTED ASSOCIATIONS

1% growth in factor indicated	% growth in non-aeronautical revenue
passenger numbers	0.7 - 1.0
size of commercial area	0.2
global passenger satisfaction mean	1.5

One of the challenges of constructing a comprehensive model for an airport is to try to build causal relationships between a small number of core variables. The choice of these variables should be done by considering how much the different variables are dependent on each other in the data. The first step to do this is to compute the correlation coefficients between each variable, which give the magnitude of the linear statistical correlation between them. For simplicity, we do not display all the coefficients but we describe hereafter the main conclusions.

The operating revenues are very well correlated with several metrics, including the number of passengers and the number of flights, which is expected, but also with the aircraft occupation (number of passengers per flight) and the number of passengers per route, with correlation coefficients as high as 0.97. This is especially striking because the latter metrics are not trivially linked to the number of passengers and the number of flights, so it is not a simple scaling effect. In fact, it shows how 'extensive' variables, i.e. scaling (in first approximation) with the number of passengers or

flights, can interact with ‘intensive’ variables. These effects are very important to capture, because intensive variables usually capture the fundamental organisation of the system, related to the interaction between different agents (e.g. some kind of management rule). Regarding the precise meaning of this correlation, it is not clear at this stage why the operating results should be so closely related to these metrics, except if they are linked to some kind of capacity, as we show in the following.

More interestingly, we see that some of the intensive variables, like aircraft occupancy (number of passenger per flight), are correlated with the size of the airport (0.61). This is also expected since small airports usually have more versatile functionality, which requires smaller aircraft for flexibility. Other features are worth exploring. For instance, the fraction of flights operated within Europe seems to be highly (anti-)correlated with different variables, including the total number of flights, number of gates, etc., (-0.77 and -0.65, respectively). This was expected since intercontinental airports are also the biggest ones. More importantly, total delays seem to be positively correlated with the number of runways, the number of gates and the number of terminals (0.41, 0.58, and 0.45, respectively), i.e. with the size of the infrastructure. This is because bigger delays are expected at the bigger airports, which have the largest infrastructure. On the other hand, the delay per flight is less correlated with the infrastructure (0.38, 0.34, and 0.2). This is a good sign, because it could mean that the airports increase their infrastructure to counterbalance delays. We may also note that runway and terminal usages have non-trivial behaviour with respect to the *number* of runways and terminals, since, they are weakly or negatively correlated with them (-0.25 and 0.02), which could loosely mean that average airports are ‘over-building’, i.e. the number of runways and the number of terminals increase more quickly than the number of passengers. Note that, strangely, the terminal usage increases (weakly) with the number of runways (0.25), whereas the runway usage is quite independent of the terminal usage. This is the product of a subtle coevolution of different capacities, namely the terminal capacities and the runway capacities.

Indeed, this is typically where simple correlation scores begin to show their limit. It is not clear at this point what are the drivers of the different metrics and whether a few causes only can explain most of the correlations. In order to explore this, we turn to principal components analysis.

2) *Principal components analysis*: Principal components analysis (PCA) determines whether it is possible to describe observed variables using a smaller number of unobserved variables. PCA removes correlations from a set of observed variables and produces a set of uncorrelated variables called ‘principal components’, linearly related to the initial variables. These components are mathematical functions of the observed variables whereby we need not assume the existence of underlying, hypothetical factors. The objective is to explain as much variance as possible in the data, and this is generally a key indication of the quality of the solution. However, it is not acceptable to obtain a purely ‘mathematical’ solution in the analysis, i.e. whereby the analyst is not able to assign

real meaning to the factors, which may be a challenge when there are too many of them. There is thus usually a trade-off between the number of components and the amount of variance explained. The analyst often ‘rotates’ the factors, to increase loadings on some of the original variables, and decrease them on others, in order to ease the interpretation of the solution and improve its simplicity. In order to allow a better interpretation of the results, we use varimax rotation. This is an orthogonal rotation method that minimises the number of variables with high loadings on each factor [34].

Running the PCA on the variables presented above, we extracted four components, which explain approximately 78% of the variance (46%, 9%, 14% and 9%, respectively, in the different panels of figure 2). These figures show the contribution of each initial variable to the ‘hidden’ variables.

The first component (labelled 0) is homogeneously composed by all initial variables, in particular the ‘extensive’ variables such as the total number of flights or the number of delays. Hence, this first variable can be seen as the ‘size’ of the airport, which appears to be the main driver of most of the initial variables, because this first component accounts for almost half of the variance.

The result for the second component (labelled 1) is displayed on the second panel of figure 2. This one is clearly linked to the type of airlines which are operating at the airport. Specifically, it seems that 9% of the variance is closely linked to the fact that airports serve more traditional companies or more low-cost companies. It is also clear that the infrastructure is closely linked to this, since the number of runways and terminals play a large role in this component too. Also interesting, the component is linked to the number of passengers per aircraft, which is low when the component is low, i.e. when the airport is more ‘low-cost-oriented’ – in spite of pressures on these airlines to be punctual and have minimal turnaround times. This is not unexpected, since low-cost companies often operate smaller aircraft as they have very little long-haul traffic. It is also worth noting that the delay per flight increases when the airport is more ‘low-cost-oriented’.

The third component (labelled 2) is presented in the third panel, and is clearly related to the financial state of the airport, with net basic utility and non-aeronautical revenues playing a major role. Interestingly, the total number of runways impacts positively on this component, whereas the number of terminals has a negative effect. Since the capacity we are measuring is linked to the air traffic movements, it is clear also that it affects the component accordingly with the number of runways.

Finally, the last component (labelled 3), presented in the last panel of figure 2, is linked to the physical infrastructure of the airport, which impacts also its usage (number of flights per runway and per terminal), but also the passenger satisfaction.

A full review of the implications of the results of the PCA is beyond the scope of this article, although they do fit with some of the preconceptions found in the literature and are roughly aligned with the ‘expert’ point of view. However, it is interesting to note that non-trivial insights can be also extracted from the analysis. For instance, the type of traffic

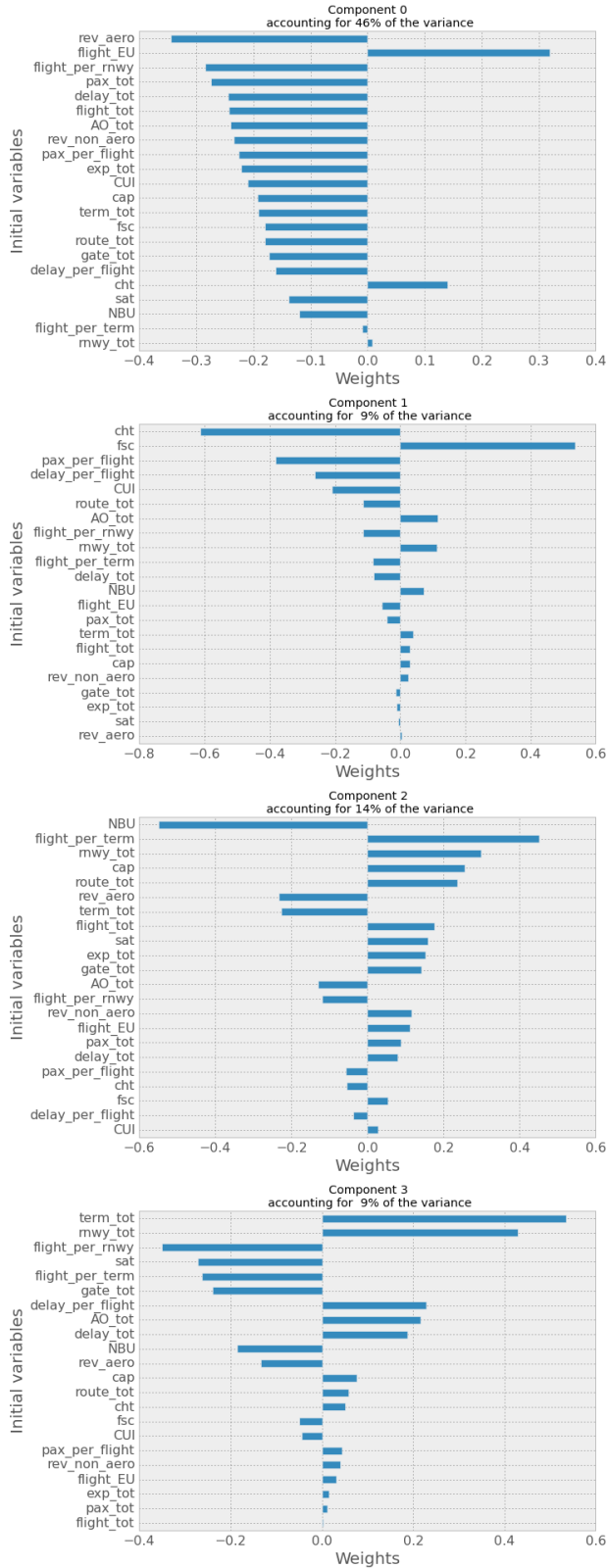


Figure 2. The four components of the PCA.

mix is closely related to the number of passengers per flight, the delay per flight, and the Capacity Utilisation index (see second component, labelled ‘1’). Since size has already been taken into account by the first component, this result is not trivially linked to the size of the airport but rather to the business models of the airlines. The same is true for the third component (labelled ‘2’), where we see that the net basic utility of the airport (broadly its net income) is negatively linked to the number of flights per terminal. Why would a purely financial component be linked to this variable, when the size has already been accounted for? This is clearly linked to the management of the airport and may be due to diseconomies of scale (because of the negative weight in the NBU).

B. Airport cluster analysis

1) *Methodology*: One key aspect of any model is to reduce the complexity of a number of mechanisms directly coming from reality into a small set of representative features. In order to build a comprehensive model, we used a clustering analysis to collect the airports into different groups. The idea is to guide the modelling process and also to be able to ‘switch’ between different kinds of behaviours when using the model.

There are many different ways of clustering data, each corresponding to the definition of ‘clustering’. Several methods are routinely used in the literature but the specific choice of method is always quite subjective. In this article, we decided to use a technique coming from network theory, based on modularity. If we consider a network with an adjacency matrix A and a partition P of its nodes, the modularity is defined as:

$$Q = \frac{1}{2m} \sum_{C \in P} \sum_{i,j \in C} (A_{ij} - P_{ij}), \quad (1)$$

where P_{ij} is the expected value of the adjacency matrix for the link i, j , and m is the total weights of the links. The modularity is typically a measure of how much the nodes are tightly linked to each other within the communities (clusters), with respect to how much they are linked with the rest of the network. The null model for the matrix is usually the one proposed by Newman and Girvan [35]: $P_{ij} = k_i k_j / 2m$, which corresponds to a randomization of the links, conserving the local strengths. One then needs to find the partition P of nodes which maximizes the modularity, and for this several algorithms exist. In this article we use the Louvain method, which is very efficient and widely used [36].

It is well known that the modularity suffers from a resolution issue, but there is an easy and elegant way to circumvent this, by adding a scaling term to the null model’s matrix, i.e. $P_{ij} = \gamma k_i k_j / 2m$. If γ is high enough, one obtains typically very small communities (down to the size of one node each). A small value means on the other hand that the partition maximizing the modularity is the one where all nodes are in the same partition. In between, one spans different levels of granularity of the system. If there is again a certain degree a subjectivity in the choice of the right scale, one is strongly guided by the appearance of plateaus in the number of clusters when sweeping the scale – as shown hereafter.

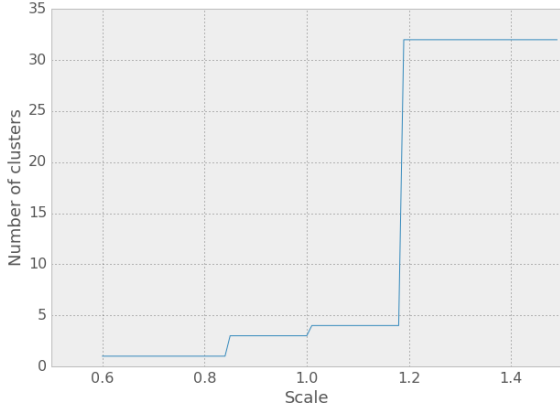


Figure 3. Number of communities in the network of airport as a function of the scaling parameter. The presence of plateaus indicates the existence of natural cluster structure at these scales.

In order to use this method, the data must be organized in some kind of network. A typical approach is to define a degree of similarity – or distance – between airports. Several choices are possible, but a common choice is to use the Euclidean distance on standardised data, i.e. computing:

$$d_{ij} = \sqrt{\sum_k (c_i^k - c_j^k)^2}, \quad (2)$$

where c_i^k is the standardised value of the component k for airport i . The components are indeed standardised as follows:

$$c_i^k = \frac{\tilde{c}_i^k - \min_j \tilde{c}_j^k}{\max_j \tilde{c}_j^k - \min_j \tilde{c}_j^k}, \quad (3)$$

which means that all components span the interval $[0, 1]$. Note that one can also put different weights on different components, to better reflect either their importance or some prior knowledge on the data.

In this study we use the components of the PCA to enter into the distances between airports, instead of the initial variables, which reflect a the natural organisation of the data. Moreover, we use the relative variance weights of each component in the Euclidean distance, i.e. $d_{ij} = \sqrt{\sum_{k=0}^3 w_k (c_i^k - c_j^k)^2}$, where w_k is the ratio of variance explained with component k .

In summary, we define a certain number of components (the same that we used for the PCA), we build a network where each node is an airport and each pair of airports has links of strength $1 - d_{ij}$, we sweep the parameter γ and for each value we compute the best partition with the Louvain algorithm. In the following subsection we show the result of the procedure.

2) *Clusters of airports*: The first step is to check if there are some scales for which the system has a non-trivial number of clusters. Figure 3 shows indeed the existence of plateaus when one sweeps the scaling parameter, more specifically a plateau with 3 communities and another one with 4 of them.

We then check that these plateaus actually correspond to stable partitions and not, for example, to sequences of different partitions with the same number of clusters. The procedure we use is to compute the Normalised Mutual Information (NMI) – a measure of similarity between partitions – and check that it is close to 1 throughout the plateau. We also checked that, when perturbing slightly the data, the partitions were not changing too much (results not shown here).

We then inspect the partitions themselves. In table III we display the composition of the 3-cluster partition. We firstly compare this partition with the 4-cluster partition (not shown), which is, in fact, very similar. The only difference is the presence of a new cluster containing two airports (Copenhagen and Vienna) otherwise in cluster number 2. Since the operational meaning of this small cluster is not obvious, we focus in this paper on the 3-cluster partition. Intuitively, the partition seems to make sense. Cluster 1 includes mostly major hubs, whereas clusters 0 and 2 include airports with less traffic. Indeed, cluster 2 contains a number of secondary hub airports.

In order to inspect the clusters more closely, we show in table IV the average value of each of the airports' characteristics, according to three categories: low, medium and high. Upon inspection of the table, the difference between clusters 0 and 2 appear more clearly. Indeed, the first one includes airports which have proportionally lower delays per flight, fewer routes, lower passenger satisfaction, fewer flights, and less congestion (CUI) with respect to cluster 2. The table also confirms the status of 'hubs' of the airports of cluster 1, with high numbers of passengers, high numbers of flights, high revenues and expenses. It confirms a tendency of hubs to attract non-low-cost carriers, to produce higher delays per flight, and to have a more international profile. Interestingly, the passenger satisfaction is also different in this cluster, even if we cannot disclose even its average level, due to an agreement with ACI. The net basic utility is not so high, however, probably driven by higher delays per flight, whereas the load factor is also high for hubs, as expected.

This clustering analysis will be included in the model at a later stage by having different functional relationships for airports belonging in different clusters.

IV. BUILDING THE GENERIC MODEL

A. Principles of the modelling process

The model we present in this article is a simple functional model based on representative agents. To build the model, we considered the following relevant mechanisms:

- Airline revenue is primarily a function of ticket price and passenger volumes (excluding cargo). These will be influenced by the airport location, degree of competition, airline networks, airline costs and other factors. Airport congestion can cause delay costs and airport capacity increases can cause rises in airport charges. These additional costs will have a direct impact on airline revenues.
- The revenues of the airport depend on the number of flights departing and arriving (primary driver for aero-

TABLE III
COMPOSITION OF THE PARTITION FROM THE CLUSTERING ANALYSIS.

Cluster Id	ICAO Code	Airport Name
2	EBBR	Brussels
	EDDL	Dusseldorf
	EGCC	Manchester
	EIDW	Dublin
	EKCH	Copenhagen Kastrup
	ENGM	Oslo Gardermoen
	ESSA	Stockholm Arlanda
	LOWW	Vienna
	LPPT	Lisbon
1	EDDF	Frankfurt
	EDDM	Munich
	EGKK	London Gatwick
	EGLL	London Heathrow
	EHAM	Amsterdam Schiphol
	LEBL	Barcelona-El Prat
	LEMD	Adolfo Suarez Madrid
	LFPG	Paris Charles de Gaulle
	LIRF	Rome Fiumicino
	LSZH	Zurich
	LTBA	Istanbul Ataturk
0	EDDH	Hamburg
	EDDK	Cologne Bonn
	EFHK	Helsinki
	EGBB	Birmingham
	EGSS	London Stansted
	ELLX	Luxembourg
	EPWA	Warsaw Chopin
	LFMN	Nice Cote d'Azur
	LGAV	Athens
	LHBP	Budapest
	LKPR	Prague
	LPPR	Porto

TABLE IV
AVERAGE VALUE OF EACH CHARACTERISTIC WITHIN EACH CLUSTER (L=Low, M=MEDIUM, H=HIGH). THE AVERAGE LEVEL OF SATISFACTION CANNOT BE DISCLOSED DUE TO AN AGREEMENT WITH ACI, BUT ARE DIFFERENT IN EACH CLUSTER.

	0	1	2
AO_tot	L	M	M
CUI	L	M	M
NBU	H	M	H
cap	L	H	M
cht	M	L	M
delay_per_flight	L	M	M
delay_tot	L	M	L
exp_tot	L	M	L
flight_EU	H	M	M
flight_per_rnwy	L	M	M
flight_per_term	L	M	L
flight_tot	L	H	M
fsc	M	H	M
gate_tot	L	M	L
pax_per_flight	M	H	M
pax_tot	L	M	L
rev_aero	L	L	L
rev_non_aero	L	M	L
rnwy_tot	L	M	L
route_tot	L	M	M
sat	*	*	*
term_tot	L	L	L

nautical revenues³) and the total number of passengers (a primary driver for non-aeronautical revenues). Their costs are mainly driven by the upkeep and the development of new capacity facilities and not by major operational changes, e.g. related to more stringent security controls.

- The passengers' choices are primarily determined by external factors (e.g. airport location, airline fare/service) and thus are not modelled here. However passengers have different experiences at different airports, based on the delay at the airport, the quality of service at the airport, etc., that we collectively collect under the term 'utility'.
- The delay is a direct consequence of the congestion at airport.

Based on these considerations, we choose the following core mechanisms for the model. The first variable we consider is the capacity C of the airport, which, compared to the level of traffic T , produces a certain level of delay δt at the airport. Based on this delay, a cost of delay c_d for the airline is derived. Together with the airport fees P , this produces the net income of the airline in our model. In order to have a market response coming from the delay, and ultimately the capacity, we assume that the airline then has a probability P_a of actually operating the flight, increasing with its income. The airport itself has a net income based on its aeronautical revenues $r_{A,aero}$, proportional to the number of flights actually operated, its non-aeronautical revenues $r_{A,non-aero}$, proportional to the number of passengers, and its operational cost c_{inf} , which is a linear function of the capacity. The non-aeronautical revenues are based on the average passengers' spending w at the airport, which increase with the mean delay δt . Finally, in order to see the impact of the delay on passengers, we introduce a utility u_p for the passengers, which is also a function of the delay.

In the following, we describe the specific equations that we used in the model, following the mechanisms described above.

The first functional relationship that we use aims at linking the delay at an airport with respect to the capacity and the traffic. We choose the following form:

$$\delta t = \begin{cases} 0 & \text{if } T < C \\ d_0 \frac{e^{\frac{T-C}{C}} - 1}{e - 1} & \text{otherwise,} \end{cases} \quad (4)$$

where C is the capacity of the airport, T is the traffic (see next section for their exact meaning, like the time frame), and d_0 is a parameter, which represents the delay at the airport when it operates at double capacity.

For the revenue impact of the airline, we simply take into account the losses due to delays and airport charges, and consider the prices as being fixed as external parameters. Hence, the revenue impact of the airlines is given by:

$$r_a = -c_d(\delta t) - P, \quad (5)$$

³Strictly speaking, the primary drivers of aeronautical revenues for most airports are the passenger charge and weight of the aircraft. However, the model considers a constant load factor per airport, and an average weight of aircraft, and so the aeronautical revenues are directly proportional to the number of flights.

where c_d is a cost of delay function, dependent on the delay δt , and P is the average airport charge (per flight). The cost of delay to the airline comprises passenger, fuel, maintenance and crew costs. The passenger costs include compensation and duty of care, etc., as required by Regulation 261 [37], and also market share costs arising from reduced punctuality (they do not include (internalised) passenger value of time costs). The delay costs are sourced from [3].

In order to model the loss of potential revenues for the airport when the congestion or the airport charges are high, we introduce a probability that the flight is actually operated at the airport, based on the expected revenues (or loss) from equation 5. Given the revenues r_a , the airline has a probability P_a of operating a flight at the airport given by:

$$P_a = c_f(r_a), \quad (6)$$

where c_f is a choice function. For this function, we use a simple hyperbolic tangent function. Shifted, this varies between 0 and 1: $c_f(r_a) = 1/(1 + \exp(-(r_a - r_0)/s))$. This choice is motivated by the fact that this probability is linked to some form of utility function for the airline, taking into account other (strategic) parameters (as described above). It allows us to have a smooth function which varies continuously between 0 and 1, and to have a risk aversion of the agent which can directly be linked to the parameter s – henceforth referred to as the ‘smoothness’ of the decision. Indeed, when s is sufficiently small, the airline takes harsh decisions, switching from operating to non-operating the route once revenues are driven low enough. Note that, in fact, we would strictly be referring to net revenue contribution to the network, since airlines will tolerate loss-making legs that have a net benefit to the system.

Moreover, we are able to introduce with this function an element of prospect theory, in the sense that the utility of the airline does not depend only on its revenues, but also on a pre-determined level r_0 (some kind of ‘anchoring’). This parameter includes the direct revenues from the passengers (prices of the tickets, etc.) and other costs linked to the operation. In our model, this parameter is an external one, which needs to be calibrated on data (through post-calibration, see section IV-B). Finally, this function mimics standard functions from prospect theory, since it is convex in the positive region (revenues greater than the value anchor) and concave otherwise.

Regarding the airport, we assume that its revenues come from aeronautical revenues and non-aeronautical revenues. The former depends on the airport charges P and the potential number of flights operated N , with $r_{A,aero} = PNP_A$, where P_A is the probability that they actually operate. The latter is directly linked to the number of passengers, $r_{A,non-aero} = l_f w NP_A$, where l_f is the average load factor and w is the average revenue coming from each individual passenger. The first one is a constant in our model, that we calibrate directly on data, whereas w is a function of the delay at the airport,

which we choose to be linear within a certain range:

$$w = \begin{cases} s_{max} \frac{\delta t}{t_1} & \text{if } \delta t < t_1, \\ s_{max} & \text{if } \delta t \geq t_1. \end{cases} \quad (7)$$

In other words, the passenger spends s_{max} if his/her flight has a large delay, but otherwise spends an amount which grows linearly with time.

Finally, we consider the expenses of the airport. Since we are interested in capacity-related costs, we choose a very simple form for the capacity, essentially accounting for the fact that extra capacity usually needs investment in the form of physical infrastructures. The cost function reads:

$$c_{inf} = \alpha l_f (\mathcal{C} - \mathcal{C}_{init}), \quad (8)$$

where $\mathcal{C} - \mathcal{C}_{init}$ represents the increase in capacity wanted by the airport, and α is the marginal operational cost of capacity per passenger.

Because the cost of delay is non-linear with respect to the delay (see next section), we take into account the heterogeneity of the traffic, and thus the heterogeneity of the delays along the day. This allows for a better assessment of the total cost of delay for the airlines, since high delays at peak-time are counting proportionally much more than the small delays during off-peak time. Hence, equations 4 to 7 are in fact evaluated with a distribution of their arguments. For instance, based on a distribution of traffic $\{T\}$, we generate a distribution of delays $\{\delta t\}$ with equation 4, which turns into a distribution of revenues with equation 5, and so on.

In order to compare the consequences of the model for the different actors, we also compute a utility for the passengers:

$$u_p = -v\delta t + \sigma, \quad (9)$$

where v is the average value of time of the passengers and sigma is the level of satisfaction of the passengers at the airport. This is a very crude approximation, and the computed utility has no intrinsic meaning, but is nevertheless useful to compare different situations where delays are different and passengers are likely to be satisfied at different levels. Note that in this paper we do not compare the results of the model for different airports and the parameter σ does not need to be evaluated.

B. Calibration

In this section we describe how we calibrate the model. The calibration itself is done in different steps. Indeed, some parameters can be calibrated directly from the data, but some need to be swept, matching the output of the model to some values extracted from the data. Moreover, we need different functional relationships coming directly from data.

1) *Functional relationships*: Using the costs of delay introduced earlier, we carried out a regression fit for *primary* delay (to avoid double-counting across the network by including reactionary impacts) costs using the weights of the aircraft and the delay durations (as per the method established in [3]). The final function is:

$$c_d = -7.0 \delta t - 0.18 \delta t^2 + (6.0 \delta t + 0.092 \delta t^2) \sqrt{MTOW}, \quad (10)$$

For the model, we set \sqrt{MTOW} to the average across all aircraft departing the airport.

Another functional relationship is the equation presented in 4, which should be directly calibrated on data. In the present paper, we only estimate roughly the parameter d_0 to 120 minutes.

2) *Direct calibration of parameters:* Some parameters can be directly estimated from the data. Among them, the average load factor l_f , the average \sqrt{MTOW} , and C_{init} – which is the current capacity of the airport – are directly taken from data. The traffic distribution, in terms of traffic per hour, is also extracted directly from traffic data (DDR data).

The value of time of passengers, not useful *per se* for the model but impacting the passengers’ satisfaction, can be found in the literature too. To have a more realistic description, we decided to use two values of time, which are usually associated with business – v_b – and leisure passengers – v_p , taken from [38]. We then consider that most passengers on low-cost aircraft have a lower value of time – associated more often with leisure-purpose trips – whereas passengers (on average) travelling with traditional airlines have a higher value of time overall – including more business-purpose trips. As a consequence, the average value of time in our model is:

$$v = v_l r_{lcc} + v_b(1 - r_{lcc}),$$

where r_{lcc} is simply the share of low-cost companies at the airport. This value is also directly taken from data (from DDR data).

Finally, an important parameter is the operational marginal cost of extra capacity per passenger α . This value is difficult to estimate without further data on the airports. As a consequence, we consider it to be a free parameter. Note that in order to make comparisons within the model, it can also be roughly estimated from the total operational cost *versus* the capacity at the airport, since the main task of the airport **is to deliver capacity**. However, such a value is clearly overestimated and would only provide a broad idea of the magnitude of α , or as an upper bound. In the following, we do not show this evaluation, but it can be found – together with an updated version of the model – in the final deliverable of the project [39].

3) *Post-calibration of parameters:* We call post-calibration the operation of running the model with different values of parameters, and comparing some results of the model with values extracted from the data.

We begin with the capacity of the airport. Since the ratio between capacity and traffic sets the delay in our model and that we already have the distribution of traffic, we set the capacity so that the distribution of delay produced by equation 4 matches the one extracted from data.

The second step is to set the ratio between non-aeronautical and total revenues. In our model, this depends only on the ratio $P/l_f w$, i.e. on the two parameters P and s_{max} (from the function w). We keep P as a free parameter, which could also be calibrated directly on data, but we do not have this information. From financial data however, we know the ratio

between non-aeronautical and total revenues, so we can sweep s_{max} in the model for matches with this number.

The third step is to sweep the parameter r_0 in order to match the total revenues of the airport with those in the data.

Finally, we still have two extra parameters. The first is s from equation 6 and the second is P , which could be easily calibrated given the proper data. Table V shows a summary of the calibration procedure by displaying all the relevant parameters and how they are calibrated.

TABLE V
LIST OF PARAMETERS OF THE MODEL, WITH THEIR TYPES RELATED TO CALIBRATION. DC: DIRECT CALIBRATION (OR ESTIMATED), FP: FREE PARAMETER, PC: POST-CALIBRATED. THE LAST COLUMN PRESENTS THE VALUE OBTAINED FOR THE CALIBRATION WITH CHARLES DE GAULLE AIRPORT.

Parameter of function	Type of parameter	Value for CDG
\sqrt{MTOW}	DC	120
d_0	DC	120
l_f	DC	271
c_d	DC	function
r_0	PC	-10058
P	FP	10000
s	FP	100
s_{max}	FP	201
t_1	FP/DC	90
α	FP	-
C_{init}	DC	15.9
v	DC	43.9
T	DC	Distribution

C. Preliminary results

In this section, we show the results of the calibration of the model on a specific airport, Charles de Gaulle airport (CDG). Table V shows the values of the parameters for this airport after calibration. Note that in order to compute the traffic and the capacity, we only took into account the departing flights.

Figures 4 and 5 present some output from the model. The first shows the evolution of the revenues of the airports as a function of the capacity (per hour) and the marginal cost of extra capacity per passenger α (in euros). It is clear from the graph that usually there is an optimum of revenues for a value of the capacity which is higher than the current one for CDG. Note however that this is true only for small values of α , because otherwise the capacity is too costly with respect to the benefits and there is no optimum (other than the current capacity). As pointed out previously, we are unable to estimate the real α , but the model can directly give the level of α for which a given increase in capacity would start to be profitable for the airport. This analysis is carried out in [39] with an updated, more precise version of the model.

It is also interesting to see the benefits for the other stakeholders, i.e. the airlines and the passengers. In figure 5, we show four panels, with the revenues of the airport (top left), the revenues of the airlines (top right), the average delay (bottom left) and average spending of a passenger at the airport. These plots have been obtained for $\alpha = 1$. It is interesting to note that if the airport decides to reach its optimal capacity in this case, the average delay will drop by 80% approximately. Note also that the average spending drops

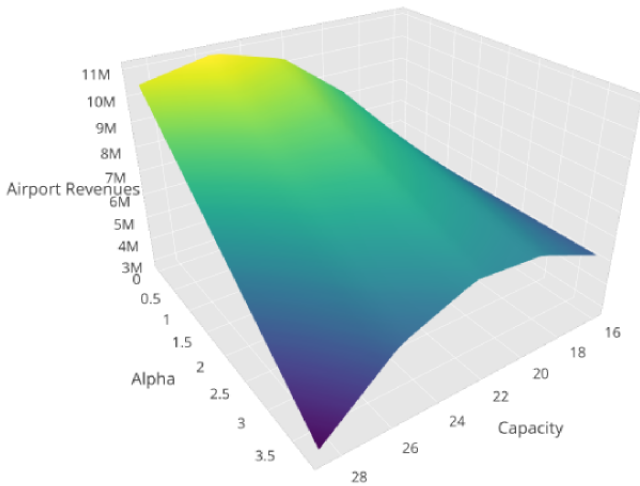


Figure 4. Daily revenues of the airport as a function of capacity (starting at current capacity) and the marginal capacity cost (Alpha).

a lot in this scenario (around 40%), which is compensated by the increase in the number of airlines operating at the airport and the number of extra passengers.

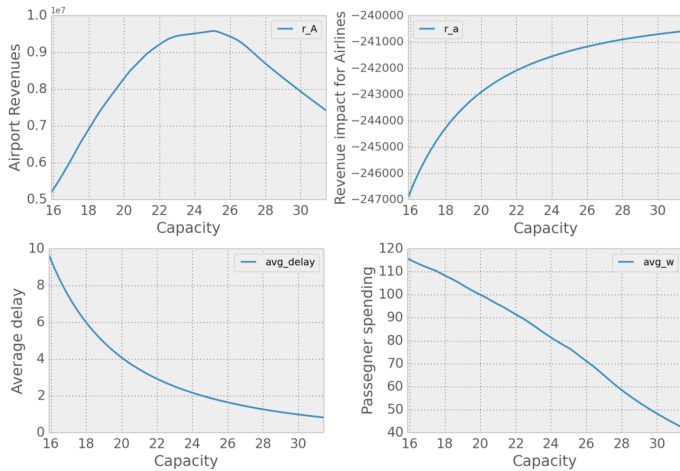


Figure 5. Revenues of the airport (top left), revenue impact for the airlines (top right), average delay (bottom left), and average spending of passengers (bottom right) as functions of the capacity. The revenues are given per day.

D. Engine implementation and user interface

The model developed in this paper is aimed at experts in the field that do not necessarily have the technical or programming skills to execute or modify a software platform. In order to make the model more accessible, a visualisation layer or graphical user interface has been developed on top of the data-driven model. The model is then delivered as an autonomous piece of software usable by a user with no programming skills.

This visualisation helps the user to understand the underlying model behaviour and evolution when varying certain input parameters and airport types, for example determining

the combination of parameters that lead to desirable outputs or, in some cases, optimum values.

The visualisation tool also helps to determine the stability and sensitivity of the optimal points, local behaviour in small neighbourhoods, visually. The engine has been developed in MATLAB and can be deployed on any java-compatible platform. It is compatible with modules (airport and airline models) written either in MATLAB or Python programming languages and exports output data into common formats: .png for figures, plus .XML and Excel-compatible CSVs for tables.

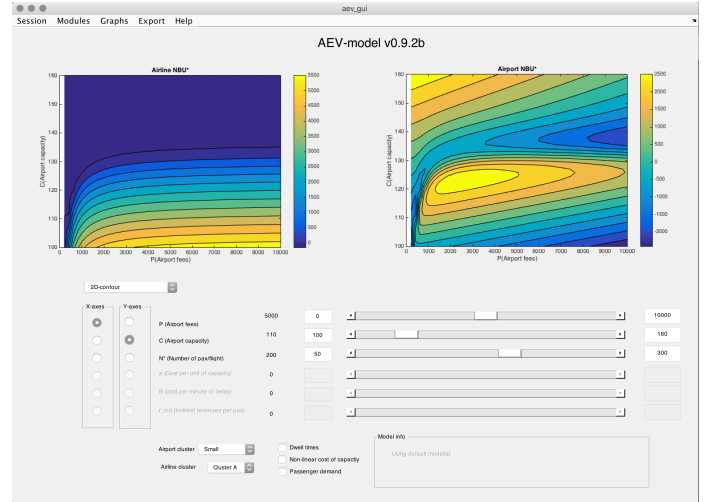


Figure 6. Screenshot of the visualization layer.

V. CONCLUSIONS AND FUTURE WORK

This study has been conducted within the context of the SESAR 1 programme. It aimed at supporting the development of the AirPort Operations Concept (APOC) by introducing an economic view of the value of an airport. By modelling and monetising a single airport economic value (using the cost of providing and utilising airport capacity, the additional revenues due to additional traffic, plus the quality of service for both passengers and flights), this study allows us to better understand the interdependencies of various KPIs and to assess the existence and behaviour of an airport economic optimum, in a similar way to the early 2000s when estimating the economic en-route capacity optimum.

Specifically, we have presented a simple but highly data-driven functional model. We have presented a concise literature review and part of the data analyses performed, both of which guided the modelling process. Indeed, one of the main challenges of this kind of model is to find a good balance between the important mechanisms at play, and the ones which can be calibrated. As a result, the literature review and the data analysis were very important, and we made several iterations, shifting our attention from one to the other in order to find the right level of description. The analysis yielded some interesting result *per se*, like the clustering analysis, which will be included in the model at a later stage.

We also showed the specific equations and relationships present in the model and how the main parameters of the model are calibrated. The mechanisms we have considered are simple enough to be calibrated, but are the core mechanisms, in our opinion, for the relevant costs and benefits of extra capacity. The calibration procedure has been built very thoroughly and will be slightly refined to include the last free parameters.

Finally, we presented some preliminary results obtained with the model calibrated on CDG. The main result for now is the presence of an optimum in capacity, at a value which is sometimes greater than the current capacity, depending on the value of the marginal cost of capacity α . It is interesting to see that not only the existence of the optimum but also its position is dependant on this value. Moreover, this value might not correspond to an achievable capacity increase, since typically the capacity has to be increased by a large amount with a large investment (new runway, new terminal, etc.), and does not vary continuously.

Overall, we believe that this model represents a valuable tool that integrates different types of data. We are confident that the final model – presented in [39] – will be useful for a cross-section of stakeholders, including regulators.

The work on APOC will continue under SESAR 2020 as part of its Project 04. In this context, it is expected that the conclusions of this study will be further refined through the introduction of additional variables and through closer interaction with interested airports. Further liaisons with ACI and with a specific airport are planned in the coming months regarding the possibility of joint modelling initiatives.

Indeed, the model clearly lacks data concerning the operational costs, and is also insufficient in terms of heterogeneity and time series. For instance, the aeronautical revenues do not take into account the different load factors, which can have a large impact on the revenues of the airports – since for some of them aeronautical revenues depend more on the number of passengers than flights. Increased effective capacity is also reached by airlines through raising load factors, as shown in the literature review. It is also important to take into account the heterogeneity among airline businesses, since expanding capacity usually does not simply increase the number of flights, but also the traffic mix. This requires more advanced modelling procedures, where economic equilibria are derived based on demand and supply functions, thus requiring more data from airlines for calibration.

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REFERENCES

- [1] EUROCONTROL, Capacity assessment and planning guidance document ed. 2.8 (2013).
- [2] P. McCarthy, US airport costs and production technology a translog cost function analysis, *Journal of Transport Economics and Policy* 48 (3).
- [3] A. Cook, G. Tanner, European airline delay cost reference values, updated and extended values, version 4.1.
- [4] T. D’Alfonso, C. Jiang, Y. Wan, Airport pricing, concession revenues and passenger types, *Journal of Transport Economics and Policy* (1) (2013) 71–89.
- [5] F. Fuerst, S. Gross, U. Klose, The sky is the limit? the determinants and constraints of European airports’ commercial revenues, *Journal of Air Transport Management* 17 (5) (2011) 278–283.
- [6] Airports Council International, Does passenger satisfaction increase airport non-aeronautical revenue? A comprehensive assessment, research report (2016).
- [7] R. Merkert, G. Assaf, Using DEA models to jointly estimate service quality perception and profitability – evidence from international airports, *Transportation Research Part A: Policy and Practice* 75 (2015) 42–50.
- [8] Y. Xiao, X. Fu, A. Zhang, Demand uncertainty and airport capacity choice, *Transportation Research Part B: Methodological* 57 (2013) 91–104.
- [9] C. Barnhart, D. Fearing, A. Odoni, V. Vaze, Demand and capacity management in air transportation, *EURO Journal on Transportation and Logistics* 1 (1-2) (2012) 135–155.
- [10] J. Martín, A. Voltes-Dorta, The dilemma between capacity expansions and multi-airport systems: Empirical evidence from the industrys cost function, *Transportation Research Part E: Logistics and Transportation Review* 47 (3) (2011) 382–389.
- [11] J. Daniel, Benefit-cost analysis of airport infrastructure: the case of taxiways, *Journal of Air Transport Management* 8 (3) (2002) 149–164.
- [12] J.-D. Jorge, G. de Rus, Cost-benefit analysis of investments in airport infrastructure: a practical approach, *Journal of Air Transport Management* 10 (5) (2004) 311–326.
- [13] M. Gelhausen, P. Berster, D. Wilken, Do airport capacity constraints have a serious impact on the future development of air traffic?, *Journal of Air Transport Management* 28 (2013) 3–13.
- [14] P. Berster, M. Gelhausen, D. Wilken, Is increasing seat capacity common practice of airlines at congested airports?, *Journal of Air Transport Management* 46 (2013) 1–25.
- [15] A. Zhang, A. Czerny, Airports and airlines economics and policy: an interpretive review of recent research, *Economics of Transportation* 1 (1) (2012) 15–34.
- [16] A. Czerny, A. Zhang, Airport congestion pricing and passenger types, *Transportation Research Part B: Methodological* 45 (3) (2011) 595–604.
- [17] A. Yuen, A. Zhang, Airport congestion pricing and its welfare implications: the case of variable passenger time costs, *Pacific Economic Review* 16 (1) (2011) 83–102.
- [18] N. Adler, P. Forsyth, J. Mueller, H.-M. Niemeier, An economic assessment of airport incentive regulation, *Transport Policy* 41 (2015) 5–15.
- [19] M. Madas, K. Zografos, Airport capacity vs. demand: Mismatch or mismanagement?, *Transportation Research Part A: Policy and Practice* 42 (1).
- [20] E. Verhoef, Congestion pricing, slot sales and slot trading in aviation, *Transportation Research Part B: Methodological* 44 (3) (2010) 320–329.
- [21] B. Desart, D. Gillinwater, M. Janic, Capacity dynamics and the formulation of the airport capacity/stability paradox: a European perspective, *Journal of Air Transport Management* 16 (2) (2010) 81–85.
- [22] E. Gilbo, Airport capacity: Representation, estimation, optimization, *IEEE Transactions on Control Systems Technology* (3) (1993) 144–154.
- [23] Y. Wan, C. Jiang, A. Zhang, Airport congestion pricing and terminal investment: Effects of terminal congestion, passenger types, and concessions, *Transportation Research Part B: Methodological* 82 (2015) 91–113.
- [24] FAA, Economic values for faa investment and regulatory decisions, a guide (2014).
- [25] A. Zhang, Y. Zhang, Airport capacity and congestion pricing with both aeronautical and commercial operations, *Transportation Research Part B: Methodological* 44 (3) (2010) 404–413.
- [26] International Transport Forum, Expanding airport capacity under constraints in large urban areas, discussion paper, 2013, p. 242.

- [27] J. Castillo-Manzano, Determinants of commercial revenues at airports: lessons learned from Spanish regional airports, *Tourism Management* 31 (2010) 788–796.
- [28] Z. Lei, A. Papatheodorou, E. Szivas, The effect of low-cost carriers on regional airports' revenue: evidence from the UK.
- [29] E. Pels, P. Nijkamp, P. Rietveld, Inefficiencies and scale economies of European airport operations, *Transportation Research Part E: Logistics and Transportation Review* 39 (5) (2003) 341–361.
- [30] J. Martin, A. Voltes-Dorta, International airports: economies of scale and marginal costs 47 (1) (2010) 5–22.
- [31] G. Bel, X. Fageda, Privatization, regulation and airport pricing: an empirical analysis for Europe, *Journal of Regulatory Economics* 37 (2) (2010) 142–161.
- [32] V. Bilotkach, J. Clougherty, J. Mueller, Z. A. A, Regulation, privatization, and airport charges: panel data evidence from European airports, *Journal of Regulatory Economics* (1) (2012) 73–94.
- [33] D. Starkie, G. Yarrow, Why airports can face price-elastic demands: Margins, lumpiness and leveraged passenger losses, *International Transport Forum discussion paper* 23.
- [34] J.-O. Kim, C. Mueller, *Factor Analysis – Statistical Methods and Practical Issues*, SAGE Publications, Newbury Park, California, 1978.
- [35] M. Newman, M. Girvan, Finding and evaluating community structure in networks, *Phys Rev E* 69 (026113).
- [36] V. Blondel, J. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, *JSTAT* (P10008).
- [37] European Commission, Regulation (ec) No 261/2004 of the European Parliament and of the Council of 11 february 2004 establishing common rules on compensation and assistance to passengers in the event of denied boarding and of cancellation or long delay of flights, and repealing Regulation (EEC) No 295/91, 17 february 2004, 1-7 (2004).
- [38] EUROCONTROL, Standard Inputs for EUROCONTROL Cost Benefit Analysis (Edition Number: 7.0, November 2015), accessed on 28.06.2016, <https://www.eurocontrol.int/sites/default/files/publication/files/standard-input-for-eurocontrol-cost-benefit-analyses-2015.pdf> (2015).
- [39] G. Gurtner, A. Graham, A. Cook, S. Cristóbal, Study on the modelling of airport economic value – final report, Deliverable 1.2 of the Airport Economic Value project, available on demand (2016).