# Ine¢ciencies and scale economies of European airport operations

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Abstract

In this paper we argue that European airports, on average, are ine¢cient. Airline ine¢ciency (low load factors) appears to contribute signi…cantly to airport ine¢ciency in terms of air passenger movements. We …nd that the average airport in Europe operates under constant returns to scale in "producing" air transport movements and under increasing returns to scale in producing passenger movements. These operating characteristics are statistically tested in a stochastic frontier model. Using data envelopment analysis, in which the number of runways is used as a …xed factor, technical and scale e¢ciency coe¢cients have been assessed. There appears to be no region-speci…c e¤ect in that an airport in a certain country or region is on average more (in)e¢cient.

## 1 Introduction

Aviation economics has become a rapidly growing branch in economic literature (see e.g. Button, 1998, and Pels, 2000). The behavior of various stakeholders in airline and airport operations is at present the subject of much theoretical and applied investigation.

Aviation has grown rapidly in recent years, and will most likely continue to grow. Moreover, various airports or governments desire to have a hub status. Airport expansion and/or the construction of new airports are therefore important policy issues in many countries. For example, Milan Malpensa is planned to become a major hub airport in Northern Italy, while Milan Linate has been for a long time the larger airport in terms of numbers of passengers and air transport movements. Linate is closer to the city center than Malpensa and is therefore more attractive to o-d passengers[1], although it has to be admitted that in the case of Linate a larger area with a high population density is exposed to aircraft noise. Linate however, covers a much smaller surface area than Malpensa, it may therefore have less growth

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[1] Note that the airport Montreal Mirabel, built to serve as an international airport, was not a success because it was too far from the city center.

potential[2]. Amsterdam Airport Schiphol faces similar problems. To accommodate the anticipated numbers of passengers (and air transport movements), Schiphol will construct a new (…fth) runway to relieve the existing runway system[3]. In addition, for the long term, other options are envisaged, one of which is moving part, or the entire, airport to a new island in the North Sea. Other airports considering expansion are e.g. Frankfurt, which is investigating the construction of a new runway, and London Heathrow, which is operating at full (or nearby full) capacity. Clearly, in the London case, there are multiple airports (most of them operated by the British Airport Authority), of which e.g. Stansted might be used to relieve Heathrow. For a detailed study, see Tolofari et al. (1990).

In this light, it is important to know whether (existing) airports are able to operate e¢ciently from an economic perspective using the current capacity, and whether or not scale economies are prevailing. In relation to that, we aim to examine whether smaller airports are equally e¢cient compared to larger airports. If not and/or if increasing economies to scale are prevailing, moving only part of the airport (e.g. intercontinental ‡ights) to a new airport (or subsidiary thereof) -one of the proposed solutions for Schiphol's future- would be unwise from an economic perspective. Then one would end up with two smaller, relatively ine¢cient airports. An airport can be labeled as ine¢cient for di¤erent reasons, the …rst of which are "indivisibilities", a well-known problem in public goods provision. An expansion of the runway system will in most cases automatically create an over-capacity, since the length of a (new) runway is mainly determined by the landing (or take-o¤) weight and speed of the aircraft using that runway. It may be necessary to construct a new runway, but due to technical (and safety) requirements, it is usually not possible to …t its capacity to the expected (additional) demand. To a lesser extent, the same holds true for airport terminals. Second are governmental regulations (e.g. limits to the hours of airport operation, noise contours) and constraints imposed by physical circumstances (e.g. fog and wind) under which airports must operate. Next to the (purely technical) ine¢ciencies described above, X-ine¢ciency also is important[4].

In this paper we focus on economies of scale in the production of airport services. In addition to these production-oriented economies, demand-related economies are also important: a large airport has the potential to o¤er higher frequencies and better and more connections in a hub and spoke network. These demand related aspects will not be discussed in this paper, although they should be kept in mind while interpreting our results. Even if economies of scale in airport operations were to be small or absent, there may nevertheless be economies on the demand side,

[2] Linate, together with Barcelona, Frankfurt, London Heathrow, London Gatwick, and Madrid were identi…ed by IATA in 1990 as the airports being the most severely limited in terms of capacity by the turn of the century (if no additional investments in capacity would be made). In total, 16 airports would be severely limited (Button, 1999).

[3] Although the technical capacity of the existing runways may be su¢cient at present, the "environmental capacity" is certainly insu¢cient; by using the existing runway system, too-large a share of the population in the surroundings may be exposed to aircraft noise.

[4] Note that "regulators" do not necessarily have an incentive to reach a social optimum. Hence, regulations can also be a cause of X-ine¢ciency.

thus implying that customers would benefit, so that consequently airports are in a better position to charge users for their services.

The determination of the economic efficiency of an airport entails the estimation of a (cost or production) frontier; an airport is (technically) efficient only if it operates on the frontier[5]. The elasticity of scale is evaluated at the frontier (even when the airport is not efficient, i.e. does not operate at the frontier). A frontier can be estimated by using parametric (e.g. stochastic frontier analysis) or non-parametric methods (e.g. data envelopment analysis (DEA)); see e.g. Pels et al. (1999) for both a DEA analysis and a stochastic production frontier analysis of European airports, and Gillen and Lall (1997) for a DEA analysis of North-American airports. Using the parametric method, one estimates a stochastic cost or production frontier. The estimation of a "standard" cost or production function fits a curve through the middle of a data cloud. Firms (airports) are on average efficient, but both positive and negative random fluctuations (with zero expected value) around the optimal production do exist. If not all firms reach the theoretical efficient frontier in practice, calibration of the "traditional" cost function will not yield the efficient frontier. To overcome this problem, a stochastic inefficiency term can be added to the traditional cost function to form a stochastic frontier. If a firm does not reach the optimal frontier (i.e. the stochastic inefficiency term is statistically different from 0), it is technically inefficient, a result that may be due to misinformation, so that wrong decisions are taken, or due to circumstances or occurrences beyond the control of the management, such as regulation or weather. According to Diewert (1992), statistical estimation of the parameters that characterize technology is more accurate using cost functions (than using production functions). However, in that case input prices are required, but there are no clear market prices for inputs[6]. A production frontier may therefore still be more useful.

DEA uses a sequence of linear programming problems to create a piecewise linear frontier, and implicitly assumes that outputs can be fully explained from the inputs. Any deviation from the efficient frontier is labeled as inefficient; random (unexplained) deviations are not possible. Stochastic production frontier analysis, conversely, determines inefficiency as the distance to the stochastic frontier; stochastic deviations from the optimal frontier are allowed.

In this paper, we use both methods as "complements" rather than as "competitors", as explained below (in Section 3). The parametric method allows for statistical testing of the presence of a deviation from the efficient frontier and returns to scale. Because DEA is non-parametric, no statistical tests are available.

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[5] Note that although a technically efficient firm generates the maximum output from a given input set, it is not guaranteed the firm uses a cost-minimizing input set or is scale efficient.

[6] One could obtain cost data from the airports' annual reports, but apart from the different accounting practices, one has the difficulty of deriving comparable input prices from aggregate cost data; even if the price of a standardized unit of, for example, terminal space could be determined for every airport, these prices could vary over the different airports for a large number of reasons (e.g. ownership, pricing policies, taxes, legal constraints, environmental controls, etc.). Another possible data source is ACI (1999), but these data are not sufficient to calibrate a meaningful cost function. See Button (1999) for a general survey of aviation data.

The outline of this paper is as follows. In Section 2 stochastic production frontier analysis and DEA is concisely discussed. In Section 3 the data and models to be estimated are presented. In Section 4 the estimation results are presented, while Section 5 concludes. This paper is based on the third chapter of the first author's dissertation (Pels, 2000).

# 2 Frontier analysis

As discussed in the previous section we use two methods for determining a production frontier, viz. stochastic frontier analysis and DEA. Each is discussed briefly here. There exists a large body of literature on both topics, see e.g. Coelli (1996a,b) and the references therein. Although both methods are similar in that they determine a frontier and inefficiency based upon that frontier, there is a significant difference. The DEA approach provides a "measurement" of inefficiency (the "Farrell approach" (Button and Weyman-Jones, 1994)). As we will explain below, the stochastic frontier approach estimates inefficiency, but it can also be used as an "explanation" for inefficiency (the "Leibenstein approach").

## 2.1 The stochastic production frontier

We have noted in the introduction that a deviation from the optimal production frontier may have a variety of causes. Using a stochastic production frontier, the production process is characterized (approximated) by a flexible functional form, while inefficiency (the deviation from the frontier) is modeled explicitly.

Consider the following stochastic production frontier:

$$
\begin{aligned}
y_{j;t} &= f\left(x_{j;t}; \exp(R)\right) \times \exp\left(E_{j;t}\right) \\
E_{j;t} &= V_{j;t} - U_{j;t}(z_{j;t})
\end{aligned}
\tag{1}
$$

where $y_{j;t}$ is the output of airport $j$ in period $t$, $x_{j;t}$ is a vector of inputs of airport $j$ in period $t$; and $R$ represents the state of technology. This is discussed in greater detail in Subsection 3.2. $f()$ is a transformation function which represents the deterministic part of the production frontier. $V_{j;t} \sim N(0; \sigma_V^2)$ and IID is a "standard" error term. $U_{j;t}$ represents the non-negative (stochastic) deviation from the production frontier; for $U_{j;t} > 0$ airport $j$ does not reach the (efficient) frontier due to technical inefficiency. $U_{j;t} \sim N(m_{j;t}; \sigma_U^2)$, truncated at 0, and $m_{j;t} = z_{j;t}\delta$. $U_{j;t}$ and $V_{j;t}$ are independent. $z_j$ is a vector of airport attributes that are not considered as inputs, but can explain inefficiency (e.g., variables representing the degree of regulation).

If equation (1) is estimated in log-log form, then the technical efficiency (

$$
TE_j = \frac{E\left(y_{j;t} \mid \hat{U}_{j;t}; x_{j;t}; z_{j;t}\right)}{E\left(y_{j;t} \mid U_{j;t} = 0; x_{j;t}; z_{j;t}\right)} = \exp\left(-\hat{U}_{j;t}\right) \tag{2}
$$

where $\hat{U}_{j;t}$ is the predicted value of $U_{j;t}$. Again, based on a log-log form, returns to scale can be determined as (see also Fuss et al., 1978):

$$RTS = \sum_j \frac{\partial y_{j;t}}{\partial x_j} \qquad (3)$$

After this brief intorcuction to stochastic frontier analysis we continue with data envelopment analysis in the next subsection. The econometric models corresponding to equation (1) are presented in Section 3.

## 2.2 Data envelopment analysis

In DEA one uses a series of linear programming problems to determine a (production) frontier. The efficiency of each airport[7] is evaluated against this frontier. Hence the efficiency of an airport is evaluated relative to the performance of other airports. Both input and output-oriented models can be used, depending on which variable is the target variable. For example, if the objective is to produce as much output as possible using the given input, one should use an output-oriented model. If the objective is to produce a given output using a minimum of inputs, an input-oriented model is more suitable. Although airports are the decision making units in this analysis, they have little control over the outputs (apart from government imposed limitations such as a 44 million passenger limit for Amsterdam Airport Schiphol); the airlines are the agents selling aircraft seats and transporting passengers[8]. Seen from that perspective, an input-oriented program seems to be more appropriate for the problem analyzed in this paper[9,10]. Note that both models estimate the same frontier, but the efficiency measures of the inefficient decision making units may be different (since the models generate the same frontier, the efficient decision making units will be the same in both models).

The efficiency measure proposed by Charnes et al. (1978) maximizes weighted outputs over weighted inputs, subject to the condition that for every airport this efficiency measure is smaller than or equal to 1. Assume that we have L airports

[7] Charnes et al. (1978), and a significant proportion of the literature that followed that paper, use the term "decision making unit" for the firm or agent analyzed to emphasize that their interest lies in the decisions made by non-profit organizations rather than (in theory) profit maximizing firms.

[8] See Pels et al. (2000) for a theoretical analysis of how an airport investment influences airline competition, and on how airline competition in turn influences airports.

[9] In the remainder of this paper, all models are input-oriented. For output-oriented specifications see e.g. Banker et al. (1984) and Coelli (1996b).

[10] One could of course also ask how much output could be generated with a given input set, including environmental capacity. This could be useful for airports like Amsterdam Airport Schiphol, where environmental restrictions are becoming increasingly important, but requires an exact definition of the input "environment", which is unavailable. Ultimately, the orientation of the model depends on the status and policy of the airport operator. These are, of course, not the same for all airports, but, in general, the input-oriented model probably suits the "average airport" best.

with m outputs and n inputs, then for an airport denoted by a subscript 0, the measure of efficiency is[11]:

$$
\begin{aligned}
&\max_{u,v} \frac{\sum_{i=1}^{m} u_i y_{i,0}}{\sum_{j=1}^{n} v_j x_{j,0}} \\
&\text{s.t. } 1 \geq \frac{\sum_{i=1}^{m} u_i y_{i,l}}{\sum_{j=1}^{n} v_j x_{j,l}}; \qquad l = 1, \ldots, L; \\
&\qquad u_i, v_j \geq 0
\end{aligned} \tag{4}
$$

The maximization problem in (4) can have an infinite number of solutions (if $(u^*, v^*)$ is a solution, so is $(\theta u^*, \theta v^*)$, see Coelli, 1996b). Charnes et al. (1978) show that the above fractional programming program has the following linear programming

$$
\begin{aligned}
&\max_{u,v} \sum_{i=1}^{m} \mu_i y_{i,0} \\
&\text{s.t. } 0 \geq \sum_{i=1}^{m} \mu_i y_{i,l} - \sum_{j=1}^{n} \nu_j x_{j,l}; \qquad l = 1, \ldots, L; \\
&\qquad \sum_{j=1}^{n} \nu_j x_{j,0} = 1 \\
&\qquad \mu_i, \nu_j \geq 0
\end{aligned} \tag{5}
$$

The dual to this linear programming problem is

$$
\begin{aligned}
&\min_{h,\lambda} h_0 \\
&\text{s.t. } \sum_{l=1}^{L} \lambda_l y_{i,l} \geq y_{i,0}; \qquad i = 1, \ldots, m; \\
&\qquad h_0 x_{j,0} - \sum_{l=1}^{L} \lambda_l x_{j,l} \geq 0; \qquad j = 1, \ldots, n; \\
&\qquad h_0, \lambda_l \geq 0
\end{aligned} \tag{6}
$$

which has fewer constraints and is therefore usually preferred in the literature[12].

Banker et al. (1984) show that the efficiency coefficient $h_0$ in (6) is the product of a technical and scale efficiency measure. Hence, if not all decision making units

[11] This maximization problem is repeated for each of the L airports.

[12] The linear programming problem in (5) has $L + 1$ restrictions; the linear programming problem in (6) has $m + n$ restrictions.

are operating at the optimal scale level, the technical efficiencies determined using the model in (6) are confounded by scale inefficiencies[13]. To overcome this problem, Banker et al. (1984) add the convexity restriction[14]

$$\sum_{l=1} \lambda_l = 1 \qquad (7)$$

to the program in (6). Call the efficiency coefficient determined by this program $h_0^{VRS}$. The difference between the two approaches is plotted in Figure 1 for the case with one input and one output.

Figure 1 about here

In this graph the efficiency of a decision making unit operating at D as determined by program (6) is $h_0 = \frac{AB}{AD}$: Adding the convexity constraint (7) to (6) yields an efficiency of $h_0^{VRS} = \frac{AC}{AD}$. Note that this efficiency coefficient is always larger than or equal to the unconstrained efficiency coefficient, as the frontier fits the data more tightly. The scale efficiency is $h_0^{scale} = \frac{h_0}{h_0^{VRS}} = \frac{AB}{AC}$; if $h_0^{scale} = 1$; the decision making unit is scale efficient: If $h_0^{scale} < 1$, the scale efficiency estimate only indicates whether or not variable returns to scale are prevailing. The direction of these returns is not determined. Whether increasing or decreasing returns to scale are prevailing can be determined by running another program, in which the constraint in (7) is changed to $1 \geq \sum_{l=1} \lambda_l$ and added to (6); call the efficiency coefficient from this program $h_0^c$. Note that the linear program used to determine $h_0^c$ cannot envelop the data more closely than the program used to determine $h_0^{VRS}$ (Ferrier and Lovell, 1990), as the latter program is the most constrained $\left(\sum_{l=1} \lambda_l = 1\right)$ and the former program is the least constrained $\left(1 \geq \sum_{l=1} \lambda_l\right)$ of the two (Banker et al., 1996). Then if $h_0^{scale} < 1$ and $h_0^c = h_0^{VRS}$, decreasing returns to scale prevail. If $h_0^{scale} < 1$ and $h_0^c < h_0^{VRS}$, increasing returns to scale prevail[15].

[13] In effect, the model in (6) assumes that all decision making units are operating at their optimal scale, even when they, in fact, may not do so.

[14] This restriction implies convexity of the production set and input requirement set. This in turn implies a quasi-concave production function (frontier) (see e.g. Varian (1992) for details).

[15] There is another approach used to estimate returns to scale. Using the linear program in (6) to determine $h_0$ (i.e. without restriction 7), $\sum_{l=1} \lambda_l^*$ estimates returns to scale, where the asterisk $^*$ means an optimal solution. If this sum is smaller than 1 (in all alternate optima), increasing returns to scale are prevailing. If this sum is larger than 1 (in all alternate optima), decreasing returns are prevailing and if it is equal to 1 (in any alternate optimum), constant returns are prevailing; see Banker et al. (1996) for details. Banker et al. (1996) show that these two alternative approaches are equivalent.

# 3 Speci…cation of the model

After the theoretical exposition in the nprevious section, we will now describe the parametric and DEA models to be estimated. We …rst present a general model of airport activities, before continuing with the econometric models to be estimated in Section 4.

## 3.1 A general model of airport activities

"An airport's primary function is to provide an interface between aircraft and the passengers or freight, including mail, being transported by air" (Doganis, 1992). From this perspective, an analysis of airport outputs requires data on air passenger movements ($APM$) and air transport movements ($ATM$), with the corresponding necessary inputs. Note that the necessary inputs for these two outputs are quite di¤erent and that it is not uncommon to model these outputs separately, see e.g. Gillen et al. (1997) and Pels et al. (1999). The airport can also be regarded as an interface between airlines and passengers rather than aircraft and passengers, although the di¤erence is ambiguous. The airlines' primary objective is to sell aircraft seats. $ATM$ is essential, but is not a goal in itself. Seen from that objective, $ATM$ can also be considered as an input from the airport's perspective. Note that as $APM$ changes, $ATM$ does not necessarily follow; the airlines can adjust the load factors or seating arrangements of their aircraft; $ATM$ can be, but is not necessarily endogenous.

Figure 2 about here

From this line of reasoning, $ATM$ can be considered as an intermediate good that is "produced" and then "consumed" in the "production" of $APM$. The various relationships between $ATM$, $APM$, runway e¢ciency and terminal e¢ciency are depicted in Figure 2. If $ATM$ is low, given the runway capacity or given the inputs, runway ine¢ciency will be high; this is estimated using the stochastic production frontier. $ATM$ is considered to be an input for $APM$. Given the terminal capacity and given the airlines' load factors, a high value of $ATM$ (corresponding to low runway ine¢ciency) corresponds to a high value of $APM$ (low terminal ine¢ciency); a positive relationship between $ATM$ and $APM$ is expected in the stochastic production frontier. If terminal ine¢ciency however, is relatively high, this could be explained by the average load factors. If load factors are low, airports "need" a proportionally large number of ‡ights (high $ATM$) to move a given number of passengers. This means that, ceteris paribus, the airport is relatively ine¢cient[16]. This ine¢ciency is, however, beyond the control of the airport authorities.

[16] Assume that an increase in $ATM$ results in an increase in $APM$ (i.e. $ATM$ is a signi…cant explanatory variable in the production function explaining $APM$). If the frequency elasticity of demand is smaller than 1, an increase in $ATM$ will likely result in a less than proportional increase in $APM$, if at all. A downward adjustment of airline load factors is likely and has a positive e¤ect on terminal ine¢ciency.

The production frontiers (and inefficiency model) will be estimated using pooled cross-section - time series data for 33 European airports between 1995 and 1997. Data on ATM and APM was obtained from the British Airport Authority. The primary source for the data on inputs is IATA (1998). This source was supplemented with ACI (1999) and personal communication with some airports. The list of European airports used in the analysis is given in Appendix A.

After this brief introduction, the parametric and the DEA model will be specified in the next two subsections. As explained above, the parametric model allows for statistical testing and can be used to explain inefficiencies. But the model used (the translog) is a second-order approximation of an unknown function (frontier). Although the approximating function may be precise at the point of approximation, the precision at more extreme data points is not clear[17]. The parametric approach will therefore be used to test for the presence of returns to scale and inefficiencies (deviations from the optimal frontier). DEA will be used for an analysis of inefficiencies and returns to scale of individual airports; because DEA fits a piecewise linear curve, it does not have the problem described above.

## 3.2 The parametric model

Based on the discussion in the previous section, we model the efficiency of an airport as follows. First, a stochastic production frontier for ATM is estimated. A stochastic production frontier for APM is then estimated, in which the predicted value of ATM is an explanatory variable. The model

$$\ln\left(ATM_{j,t}\right) = \alpha_0 + \sum_i \alpha_i \ln\left(x^{i,ATM}_{j,t}\right) + \frac{1}{2}\sum_h \sum_i \alpha_{h,i} \ln\left(x^{h,ATM}_{j,t}\right) \ln\left(x^{i,ATM}_{j,t}\right) + \gamma_1 R_j + \frac{1}{2}\gamma_2 R_j^2 + \sum_i \delta_i \ln\left(x^{i,ATM}_{j,t}\right) R_j \qquad (8)$$

where $x^{i,ATM}_{j,t}$ is the i-th input used by airport j in the "production" of $ATM_{j,t}$; the "x-variables" used are the airport's surface area, the number of aircraft parking positions at the terminal and the number of remote aircraft parking positions. $R_j$ is the number of runways. Each airport uses a number of runways which is fixed, at least in the short run; for each runway there is a corresponding interval of outputs rather than a single, optimal output. Therefore, the number of runways will be used

[17] The translog function is a flexible functional form that can achieve arbitrary scale elasticities at any data point. Once the parameters of the function are estimated, the elasticities are determined for every point along the curve. It may be that the curve satisfies curvature conditions imposed by economic theory only for a specific range (Caves and Christensen, 1980). For example, Caves et al. (1984) find that the neoclassical curvature conditions on their (estimated translog) cost function are satisfied around the sample mean and violated at extreme sample points (as a result of "dominant" second order effects). Wales (1977) has shown that such problems do not necessarily undermine the validity of the elasticities evaluated at the sample mean. Caves et al. (1984) test the robustness of the specification by fixing all the second order coefficients at 0; although that specification is rejected on statistical grounds, the coefficients of the first order effects are "remarkably similar" to the unrestricted estimates.

as a fixed factor, representing a stage of technology rather than as a "traditional" input. Amsterdam Airport Schiphol, for example, has four runways. These are closed from time to time due to environmental restrictions or weather conditions, and three of these can only be used in a single direction. The inefficiency model is

$$U_{j;t}^{ATM} = \sum_j \delta_j z_j^{ATM} \tag{9}$$

The "z-variables" explaining inefficiency include a dummy variable, which has the value 1 if the airport in question is a slot coordinated airport and a dummy, which takes the value 1 if there is a time restriction.

The model explaining $APM$ is

$$\ln\left(APM_{j;t}\right) = \beta_0 + \sum_i \beta_i \ln\left(x_{j;t}^{i;APM}\right) + \frac{1}{2}\sum_h \sum_i \beta_{h;i} \ln\left(x_{j;t}^{h;APM}\right) \ln\left(x_{j;t}^{i;APM}\right) \tag{10}$$

and

$$U_{j;t}^{APM} = \sum_j \delta_j z_j^{APM} \tag{11}$$

where $x_{j;t}^{i;APM}$ is the i-th input used by airport $j$ in the production of $APM_{j;t}$; these inputs are $ATM_{j;t}^{*} = E\left(ATM_{j;t} \mid U_j; x_{j;t}^{ATM}; z_j\right)$, the number of check-in desks and the number of baggage claim units. Other possible inputs are terminal size and number of aircraft parking positions at the terminal (as an approximation of number of gates), but specifications in which these variables are also used are rejected because of insignificance of parameters of both of these variables and the variables finally used (probably due to multicollinearity, these variables are highly correlated with the variables actually used) and unexpected parameter signs. Although we assume that $ATM$ "causes" $APM$, it is not straightforward that $ATM$ is fully exogenous. Moreover, the airport has no (direct) control over the number of air transport movements; it merely provides the capacity. Therefore, the predicted value of $ATM$ (i.e. the frontier value) is used as an explanatory variable rather than as the actual value. The variables explaining inefficiency are a time dummy as described above and secondly, the airlines' load factor. The average load factor is calculated as the weighted average of the aggregate load factors between the city in which the airport is located and a number of important destinations (Amsterdam, London, Frankfurt, Paris, Zürich and Singapore). For certain airports (in London, Milan and Paris) no specific load factors could be computed; e.g. London Gatwick, Heathrow and Stansted have the same load factor because only data on routes originating in London is available.

All data (except for the dummies) are standardized around the mean. In both models a constant and two dummy variables (for 1996 and 1997) are included. The constant estimates the difference between the (unknown) output evaluated at the mean input levels and the mean output in 1995[18]. The difference in the next two years is the constant plus the dummy variable for that year.

Data on labor, both the number of people working at the airport and working for the airport, is only available for a limited number of airports. For example, the number of people employed by the operator of FRA (Flughafen Frankfurt Main AG) in 1997 is 12,500. According to the ACI airport database, FRA is the only airport operated by Flughafen Frankfurt Main AG. The British Airport Authority (BAA) had 8,393 employees and operates, among others, Heathrow, Gatwick and Stansted (BAA, 1999). The numbers of passengers at these airports in 1997 were 58 million for Heathrow and 40 million for Frankfurt. We may assume that such numerical differences reflect differences in the way workers have been classified in the various airports. Since it is not clear how many employees are actually involved in the handling of aircraft, passengers and luggage, and because data on labor is simply unavailable for a large number of airports, this variable is not used in the analysis.

## 3.3 The DEA model

The DEA models for estimating the frontier are described in detail in Subsection 2.2, and the data are identical to those in the previous subsection. Two remarks are in order, however. First, the number of runways is used as a fixed factor. The DEA program then is (see e.g. Banker and Morey (1986))

$$\begin{aligned} &\min_{h;\lambda} h_0 \\ &\text{s.t.} \sum_{l=1} \lambda_l y_{i;l} \geq y_{i;0}; \qquad i = 1; \ldots; m; \\ &\quad h_0 x_{j;0} - \sum_{l=1} \lambda_l x_{j;l} \geq 0; \qquad j = 1; \ldots; n-1; \\ &\quad x_{j;0} - \sum_{l=1} \lambda_l x_{j;l} \geq 0; \qquad j = n; \\ &\quad \sum_{l=1} \lambda_l = 1; \qquad h_0; \lambda_l \geq 0 \end{aligned} \tag{12}$$

where the number of runways is the $n^{th}$ input. This input cannot be adjusted by the management to "fit" the output, but it is used in the determination of the frontier. If the first $n-1$ inputs can be reduced, by keeping the last input (number of runways) fixed, we find that the airport in question is not efficient. Of course

[18] Note that these were equal if $f(:.)$ would be homogeneous of degree 1 and linear.

a convex combination of all airports does not necessarily have a meaningful interpretation in our case (an airport cannot have 1.5 runways), but it should be noted that: i.) runways at di¤erent airports may be di¤erent lengths and ii.) runways are considered as categorical variables in the sense that for one (unit) input (i.e. one runway), there is a range of possible outputs (see the previous subsection). This means that a portion of the frontier will run parallel to the axis (see Subsection 2.2), and that the presence of input (runway) slacks is not necessarily an indication of an inappropriate input mix. If the slack is smaller than 1, runway capacity is not fully used, but it cannot be reduced. If it is larger than 1, there could be an inappropriate input mix in that the same output could be obtained with one less runway. Second, the DEA model does not su¤er from multicollinearity, so that, in principle, "all" available inputs can be used. However, to maintain consistency between both models, the same input set is used in both models. The only di¤erence is that in the DEA model with $APM$ as the output, the actual -rather than the predicted- value of $ATM$ is used. The DEA model has no endogeneity problem and measures e¢ciency rather than it predicts outcomes.

# 4 Estimation results

In this section the estimation results from both models are discussed. The estimations were executed using FRONTIER 4.1 and DEAP 2.1 (see Coelli, 1996a,b).

## 4.1 Estimation results from the stochastic frontier model

Estimation results for the $ATM$ model are given in Table 1. The number of parking positions (both at the terminal and remote) and the airport area are signi…cant. The …rst order e¤ects (parking positions and remote parking positions) are clearly signi…cant. The parameter of the number of runways is, however, not signi…cantly di¤erent from 0. The second order e¤ect for the number of runways (i.e. the squared number of runways) is negative, indicating that a number of runways larger than the average number (2) does not lead to an increase in $ATM$, ceteris paribus.

From the estimates of the ine¢ciency model, it appears that the slot coordinated airports are less ine¢cient and also airports with limited hours of operation are less ine¢cient[19]. One possible explanation for such a result could be given, when all inputs were multiplied with the fraction of time the airports are open. For example, when an airport is open for 18 hours a day, all inputs would be multiplied by $\frac{18}{24}$. In such a situation one could expect that the time constrained airports would be more e¢cient since during night time the unconstrained airports are likely to have little tra¢c. This approach of adjusting the input levels to the hours of operation has not been applied in this analysis; instead, the (possible) in‡uence of

[19] Both parameters are insigni…cant, although this is probably due to multicollinearity. Estimations with either of these variables does not lead to signi…cant changes of the estimated frontier or the sign of the variable in question. The variables are then signi…cant, but the log-likelihood is lower of course.

time constraints on e¢ciency is modeled explicitly in the ine¢ciency model using a dummy variable. Another explanation could be the following. The production function and ine¢ciency model together determine the output. Airports with a relatively high output (which, given the input set, can result in a low ine¢ciency) cause higher environmental pressures compared to airports with a relatively low output. Because of the environmental pressures, a political decision to impose time constraints may result. This could explain the …nding that airports with limited hours of operation are less ine¢cient. Two remarks are in order though. First, environmental pressures are not the only reason to impose time constraints. For example, when the output is simply too low at certain hours, the airport can be closed because of economic reasons. Second, in the line of reasoning above we have reversed causality; the value of the time restrictions dummy is dependent the output. This calls for a di¤erent (two-stage) estimation method, but …rst, further theoretical analysis is necessary to determine the exact relations between the variables concerned.

Estimation results for the APM-model are presented in Table 2. While the (…rst order) parameters for ATM¤ and the number of check-in desks are signi…cant, the parameter for the number of baggage claims is not signi…cant. The second order coe¢cient for the number of baggage claims is, however, signi…cant. Note that the interaction terms are not signi…cant, indicating that the inputs are not complementary. The load factors have the expected sign; as load factors increase, ine¢ciency decreases. Airline ine¢ciency (re‡ected by low load factors) is apparently carried over to airports; given ATM¤, a larger passenger ‡ow could have been possible. Again, time-restricted airports are less ine¢cient.

Table 1 and 2 about here

The role of the ine¢ciency term in the total disturbance becomes clear from the values of ° reported in Tables 1 and 2. In both models, ° is close to 1 (i.e. the variance of the ine¢ciency term is large compared to the variance of the disturbance term), indicating the signi…cance of the ine¢ciency e¤ect. This also becomes clear from the likelihood ratio test of the one-sided error; the hypothesis $H_0$ : ° = $±_0$ = ::: = $±_n$ = 0 is rejected in both cases. Hence, there is a distinct ine¢ciency e¤ect. In the following subsection, through the use of DEA, these ine¢ciency e¤ects are analyzed for individual airports.

Using the production frontier estimates and equation (3), returns to scale can be calculated. For the average airport (i.e with average inputs), the elasticities (standard errors) are 0.951 (0.065) for the ATM model and 1.209 (0.029) for the APM-model; the "average" airport is operating under constant returns to scale when generating ATM and under increasing returns to scale when moving passengers. On the basis of studies of British airports, Doganis (1992) argues that the average cost per passenger falls sharply until a passenger level of about 3 million. Based on the estimates from the APM model, there is a strong negative relation between the airport size (measured in APM) and the scale elasticity as predicted by the model; the correlation coefficient is -0.83. This indicates there is some support for the common conjecture that smaller airports operate under (strong) increasing returns to scale. The corresponding correlation coefficient in the ATM model is 0.11. As mentioned above, the translog production frontier is a second order approximation of an unknown frontier at a certain point (the average). The estimated elasticities may only be plausible in a certain range of data (around the average); see footnote 18. In fact, it appears that the airports MXP and OTP have negative estimated scale elasticities[20]. Deleting these observations and calculating the correlation coefficient between the scale elasticity and the airport size measured in ATM for 1997, only (which is the most efficient year) yields -0.09[21]. If we ignore MXP and OTP, there is a very weak or insignificant relation between the elasticity of size and airport size.

The finding that airports are operating under constant returns to scale "producing" ATM and under increasing returns to scale generating APM is not uncommon; see e.g. Gillen and Lall (1997). Although, the general picture is that the scale elasticity decreases with size (expressed in APM), a detailed analysis of efficiency (for individual airports) is made using DEA.

## 4.2 Estimation results from the DEA model

The efficiency coefficients for the ATM model are reported in Table 3. To save space, only the estimates for 1997 are given. In the second column the technical efficiency from the variable returns to scale model (i.e. the linear program composed by equations (6) and (7)) is given. For most airports efficiency increases over time (as ATM increases over time). The third column gives the scale efficiency and the last column contains the returns to scale characterization; drs means decreasing returns to scale and irs means increasing returns to scale. If an airport operates under decreasing returns to scale, the scale efficiency decreases over time (as the output increases), and if an airport operates under increasing returns to scale, the scale efficiency increases over time. If the scale efficiency is 1, there is no need for the airport to increase or decrease the scale of its operations[22]. Note that if the scale efficiency is 1, the airports in question were operating under increasing returns in the previous years (because the output and technical efficiency increased over time). If 1998 were to be added to the dataset, the (absolute) values of the

[20] In the APM model all elasticity estimates are positive.

[21] The figure for 1997 for the APM model is -0.84.

[22] Related to this, Pels et al. (1999) use DEA to determine the most productive scale size of European airports. The concept of most productive scale size is due to Banker (1984b). For a given input-output mix, the most productive scale size is the scale size at which the outputs produced "per unit" of input is maximized. The problem is that for every input-output mix, there exists a most productive scale size. This is not necessarily the optimal scale size (with a cost minimizing input mix). An airport that is operating under decreasing returns to scale can reduce its scale to increase the output per "unit of input" to reach the most productive scale size. However, it can also change its input mix. Under these circumstances the airport operates under constant or even increasing returns to scale.

efficiency coefficients would change (decrease if the output increases), and airports that were operating under constant returns to scale in 1997 will now operate under increasing returns to scale in that year, because the efficiency is evaluated relative to the most efficient decision making units.

The average technical efficiency in the ATM model (0.82) appears to be quite high; almost half of the airports are technically efficient, and GVA, MXP and STO are (very) close to the efficient frontier. Yet there are a number of airports (DUB, LYS, PRG, SXF, TXL and VIE) that have a rather low efficiency coefficient. There seem to be no region-specific effects in that airports in a one country are on average more efficient than airports in other countries. The correlation coefficient between the technical efficiency (Table 3) and the airport size measured in ATM is 0.19; there only seems to be a weak "size" effect, if any. The same conclusions hold true for the APM model (Table 4, the correlation coefficient is 0.17). The average technical efficiency in the APM model is 0.82. Although there are fewer technically efficient airports, there are also less airports with relatively low technical efficiency coefficients[23].

In Tables 3 and 4 we can see that a number of airports are operating under decreasing returns to scale. FCO, FRA, MUC and ZRH operate under (slight) decreasing returns to scale in both models. AMS, BRU, ORY and STO are operating under (slight) decreasing returns to scale in the ATM model and constant or increasing returns to scale in the APM model, while the opposite holds true for MAN. The correlation coefficient between the scale efficiency (Table 4) and the airport size measured in APM is 0.53. It should be kept in mind that scale efficiency says nothing about the orientation of the returns to scale; both increasing and decreasing returns are reported in Table 4. From Table 4 it can be seen that a number of relatively smaller airports, BLL, GOT, MXP, NUE, OTP, PRG, STN, SXF, and TRN are operating under increasing to scale and have a relatively low scale efficiency. Similarly, a number of relatively large airports, AMS, CDG, FCO, FRA, LGW, LHR, LIN, MAN, MUC, ORY, and ZRH are operating under (near) constant returns to scale or decreasing returns to scale. Hence, although the correlation between the scale efficiency and airport size (measured in APM) is apparently not very high, the finding in the previous subsection that scale elasticity decreases with airport size also becomes apparent from Table 4.

Table 3 and 4 about here

The correlation between the scale efficiency in the ATM model and the airport size (measured in ATM) is 0.18; so there is no apparent relation between scale efficiency and airport size. Whereas some of the larger airports are operating at (near) constant returns to scale (CDG, CPH, LGW, LHR and LIN) or (slight) decreasing returns (AMS, BRU, FCO, FRA, MUC and ORY), some of the smaller airports are operating at increasing returns to scale and have a relatively low scale

[23] Only GVA and LYS have a coefficient below 0.5.

efficiency (BLL, FAO, GOT, LIS, MXP, NUE, OTP, STN, SXF and TRN). There is a negative relation between the returns to scale characterization of an airport and the size of the airport (measured in ATM). In the previous section we found that this relation was negative, but very weak; judging by the correlation coefficient of -0.09, there is hardly any relation. The 10 smaller airports just mentioned are operating under strong increasing returns to scale, while larger airports are operating under near constant (increasing or decreasing) returns to scale.

Clearly, both (stochastic frontier and DEA) models have their own intrinsic problems. The stochastic frontier model has potential curvature problems (see footnote 19 and Section 4.1). The DEA model does not allow for statistical testing; it cannot be tested if the scale efficiency is statistically different from 1. The only plausible conclusion is that the average airport operates under constant returns to scale and that the smallest airports (BLL, FAO, MXP, NUE, OTP, SXF and TRN), which are responsible for 4.6% of the total traffic in 1997, are almost surely operating under increasing returns to scale. The conclusion of Subsection 4.1, that the "average airport" (i.e. an airport operating at mean input levels) is operating at constant returns to scale, is thus maintained here.

# 5 Conclusion

In this paper we have estimated production frontiers for European airports, using both stochastic frontier analysis and data envelopment analysis. From the stochastic frontier analysis, it appears that there is a significant inefficiency effect. In the ATM model, airports with a time restriction and/or slot coordination appear to be less inefficient. One could think that within the limited time frame inputs are used more efficiently, but time is not considered as an argument in the production function. With or without the limited time frame, airports need the same expected peak capacity and hence can be expected to be more inefficient when there is a time restriction. During that period the airports are closed and the capacity is not used. More research into this aspect is necessary. Inefficiency in the APM model is explained by a time restriction dummy and airline load factors; apparently, airline inefficiency is carried over to airports. This link between efficiency of airlines and airports has not yet been demonstrated in the literature as far as we know.

Based on the estimates of the stochastic frontier model, we conclude that the "average" airport is operating under constant returns to scale when handling ATM and increasing returns to scale when moving passengers; the scale elasticity is decreasing in the number of passengers (i.e. on average, smaller airports are operating under strong returns to scale and larger airports are operating under weak returns to scale). This relation is rather strong in the APM model, but is rather weak in the ATM model. Using DEA, similar conclusions are drawn, the only difference being that the relation between airport size measured in ATM and returns to scale seems to be much stronger than in the case of the stochastic frontier model. The conclusion of the analysis in this paper is that the "average" airport is operating under constant returns to scale in the ATM model and increasing returns to scale in the APM model, where the returns in the latter model are decreasing in APM. These conclusions are in line with the results found in the literature (see e.g. Gillen and Lall, 1997),

One should, however, realize that the model in this paper concerns the physical capacity of the airport. Data on the environmental capacity (determined by regulation) and schedule delays, which can or should be included in the analysis, is not available. For example, in the case of Amsterdam Airport Schiphol (and other airports), the physical capacity exceeds "environmental capacity", and a new runway is to be constructed to increase "environmental capacity", although this may not be optimal from a purely economic point of view. The physical capacity of the existing runway has not (yet) been reached. To satisfy the future needs of Amsterdam Airport Schiphol, the creation of a satellite airport in the North Sea has been suggested. Based on the …ndings of the ATM model, we may conclude that it would be impractical to "divide" the runway system, including parking positions, over the two airports. Although constant returns are likely to prevail, to a certain extent smaller airports are also likely to be more ine¢cient. Given the …ndings of the APM model, it would be unwise to divide the terminal over the two airports; increasing returns to scale are prevailing. Given our …ndings in this paper, the recent decision by the authorities (December 1999) to allow further growth at Amsterdam Airport Schiphol and to postpone the construction of a new runway annex terminal in the Noth Sea seems a one.

From the analysis in this paper it appears that, although the average airport is operating under constant returns to scale in the ATM model and increasing returns to scale in the APM model, a number of airports is operating under decreasing returns to scale. From a cost perspective these airports should decrease their scale of operations. Therefore, given the present con…gurations of these airports, a hub strategy which asks for an increase in both outputs, is not necessarily optimal. If such a strategy would be followed, a recon…guration of the airport would also be necessary, and such a strategy would also entail high costs.

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# A Airports used in the analysis

| airport | City | airport | City |
|---|---|---|---|
| AMS | Amsterdam | LYS | Lyon |
| BLL | Billund | MAN | Manchester |
| BRU | Brussels | MRS | Marseille |
| CDG | Paris - Charles de Gaulle | MUC | Münich |
| CPH | Copenhagen | MXP | Milan - Malpensa |
| DUB | Dublin | NUE | Nüremberg |
| FAO | Faro | OTP | Bucharest - Otopeni |
| FCO | Rome | ORY | Paris - Orly |
| FRA | Frankfurt | PRG | Prague |
| GOT | Göthenborg | STN | London - Stansted |
| GVA | Geneva | STO | Stockholm |
| HAJ | Hannover | STU | Stuttgart |
| HAM | Hamburg | SXF | Berlin - Schönefeld |
| LGW | London - Gatwick | TRN | Turin |
| LHR | London - Heathrow | TXL | Berlin -Tegel |
| LIN | Milan - Linate | VIE | Vienna |
| LIS | Lisbon | ZRH | Zürich |

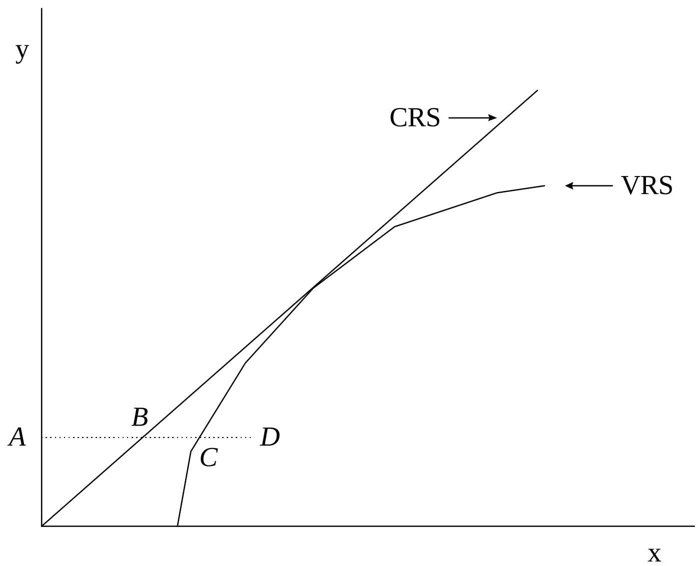


Figure 1: Production frontiers

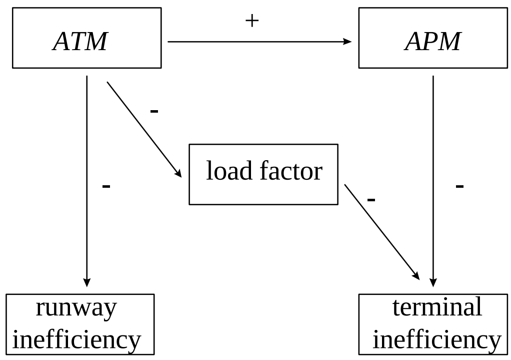


Figure 2: Relations between dependent variables and e¢ciency

Table 1 Estimation results, ATM

| Parameter | Estimate | (s.e.) |
|---|---|---|
| ®$_{constant}$ | 0.713 | (0:083)$^{¤}$ |
| ®$_{96}$ | 0.670 | (0:032)$^{¤}$ |
| ®$_{97}$ | 0.154 | (0:061)$^{¤}$ |
| ®$_{area}$ | 0.403 | (0:059)$^{¤}$ |
| ®$_{\#\ runways}$ | 0.002 | (0:115) |
| ®$_{positions}$ | 0.268 | (0:211)$^{¤}$ |
| ®$_{remote}$ | 0.280 | (0:055)$^{¤}$ |
| ®$^{2}_{area}$ | -2.207 | (0:458) |
| ®$^{2}_{\#\ runways}$ | -0.456 | (0:077)$^{¤}$ |
| ®$^{2}_{positions}$ | -0.606 | (0:130)$^{¤}$ |
| ®$^{2}_{remote}$ | -0.308 | (0:137)$^{¤}$ |
| ®$_{area£\#\ runways}$ | 0.591 | (0:068)$^{¤}$ |
| ®$_{area£positions}$ | 1.208 | (0:043)$^{¤}$ |
| ®$_{area£remote}$ | -0.090 | (0:012)$^{¤}$ |
| ®$_{\#\ runways£pos:}$ | -0.218 | (0:157) |
| ®$_{\#\ runways£rem:}$ | -0.286 | (0:128)$^{¤}$ |
| ®$_{positions£remote}$ | 0.343 | (0:152)$^{¤}$ |
| ±$_{slot\ coordination}$ | -0.278 | (0:726) |
| ±$_{time\ restriction}$ | -2.363 | (1:447) |
| ¾$^{2}_{U}$ + ¾$^{2}_{V}$ | 0:734 | (0:106)$^{¤}$ |
| ° = $\frac{¾^{2}_{U}}{¾^{2}_{U}+¾^{2}_{V}}$ | 0:999 | (0.6E-05)$^{¤}$ |
| Log-L | -10.689 | |
| LR$^{one ¡ sided\ error}$ | 73:761 | |

Table 2 Estimation results, APM

| Parmeter | Estimate | (s.e.) |
|---|---|---|
| _$_{constant}$ | 0.213 | (0:061)$^{¤}$ |
| _$_{96}$ | 0.016 | (0:041) |
| _$_{97}$ | 0.050 | (0:051) |
| _$_{ATM^{¤}}$ | 0.848 | (0:096)$^{¤}$ |
| _$_{check ¡ in\ desks}$ | 0.490 | (0:160)$^{¤}$ |
| _$_{baggage\ claims}$ | -0.129 | (0:191) |
| _$^{2}_{ATM^{¤}}$ | -0.586 | (0:162)$^{¤}$ |
| _$^{2}_{check ¡ ins}$ | -0.851 | (0:772) |
| _$^{2}_{baggage\ claims}$ | -0.905 | (0:268)$^{¤}$ |
| _$_{ATM^{¤}£check ¡ ins}$ | 0.353 | (0:477) |
| _$_{ATM^{¤}£bag:\ claims}$ | 0.209 | (0:469) |
| _$_{check ¡ ins£bag:\ claims}$ | 0.436 | (0:561) |
| ±$_{constant}$ | 0.815 | (0:562) |
| ±$_{time\ restriction}$ | -0.592 | (0:222)$^{¤}$ |
| ±$_{load\ factors}$ | -1.454 | (0:119)$^{¤}$ |
| ¾$^{2}$ | 0:377 | (0:064)$^{¤}$ |
| ° | 0.999 | (0.5E-07)$^{¤}$ |
| Log-L | -32.252 | |
| LR$^{one ¡ sided\ error}$ | 36.81 | |

Table 3 DEA efficiency results, ATM[1]

| airport | technical | scale | rs |
|---|---|---|---|
| AMS | 0.804 | 0.767 | drs |
| BLL | 1 | 0.515 | irs |
| BRU | 0.755 | 0.760 | drs |
| CDG | 1 | 1 | - |
| CPH | 1 | 1 | - |
| DUB | 0.442 | 0.830 | irs |
| FAO | 1 | 0.294 | irs |
| FCO | 0.880 | 0.850 | drs |
| FRA | 1 | 0.909 | drs |
| GOT | 1 | 0.493 | irs |
| GVA | 0.993 | 0.669 | irs |
| HAJ | 0.819 | 0.689 | irs |
| HAM | 0.650 | 0.864 | irs |
| LGW | 1 | 1 | - |
| LHR | 1 | 1 | - |
| LIN | 1 | 1 | - |
| LIS | 0.760 | 0.612 | irs |
| LYS | 0.368 | 0.768 | irs |
| MAN | 0.794 | 0.821 | irs |
| MRS | 0.699 | 0.702 | irs |
| MUC | 1 | 0.942 | drs |
| MXP | 0.955 | 0.316 | irs |
| NUE | 1 | 0.506 | irs |
| OTP | 0.734 | 0.199 | irs |
| ORY | 0.601 | 0.921 | drs |
| PRG | 0.541 | 0.673 | irs |
| STN | 0.614 | 0.595 | irs |
| STO | 0.999 | 0.821 | drs |
| STU | 1 | 1 | - |
| SXF | 0.504 | 0.275 | irs |
| TRN | 1 | 0.272 | irs |
| TXL | 0.516 | 0.883 | irs |
| VIE | 0.518 | 0.998 | irs |
| ZRH | 1 | 0.983 | drs |

Table 4 DEA efficiency results, APM

| airport | technical | scale | rs |
|---|---|---|---|
| AMS | 0.788 | 1 | - |
| BLL | 0.971 | 0.461 | irs |
| BRU | 1 | 1 | - |
| CDG | 0.695 | 0.991 | irs |
| CPH | 1 | 1 | - |
| DUB | 0.932 | 0.963 | irs |
| FAO | 1 | 0.996 | irs |
| FCO | 1 | 0.995 | drs |
| FRA | 0.809 | 0.998 | drs |
| GOT | 0.972 | 0.593 | irs |
| GVA | 0.448 | 0.951 | irs |
| HAJ | 0.674 | 0.928 | irs |
| HAM | 0.643 | 1 | - |
| LGW | 0.954 | 1 | - |
| LHR | 1 | 1 | - |
| LIN | 1 | 1 | - |
| LIS | 0.707 | 0.886 | irs |
| LYS | 0.513 | 0.970 | irs |
| MAN | 0.774 | 0.990 | drs |
| MRS | 1 | 0.970 | irs |
| MUC | 0.757 | 0.994 | drs |
| MXP | 0.842 | 0.771 | irs |
| NUE | 0.917 | 0.494 | irs |
| OTP | 0.949 | 0.401 | irs |
| ORY | 0.927 | 1 | - |
| PRG | 0.672 | 0.785 | irs |
| STN | 0.711 | 0.748 | irs |
| STO | 0.896 | 0.988 | irs |
| STU | 0.923 | 0.836 | irs |
| SXF | 1 | 0.507 | irs |
| TRN | 0.750 | 0.601 | irs |
| TXL | 0.687 | 1 | - |
| VIE | 0.798 | 0.911 | irs |
| ZRH | 0.986 | 0.988 | drs |

1 rs = returns to scale, irs = increasing returns to scale, drs = decreasing returns to scale