

EVALUATING THE EFFICIENCY PERFORMANCE OF AIRPORTS USING AN INTEGRATED AHP/DEA-AR TECHNIQUE

Abstract

Airport efficiency is an area of increasing interest to academics, policy makers and practitioners. This has resulted in a body of literature applying various econometric techniques to compare efficiency between different samples of airports. This paper uses the multi-criteria decision making method Analytic Hierarchy Process (AHP) to incorporate the weightings of input and output variables into Data Envelopment Analysis (DEA) and Assurance Region DEA (DEA-AR) models, with 24 major international airports in the empirical analysis. The paper concludes the discriminatory power in the proposed AHP/DEA-AR model is greater than in the basic DEA model when measuring the efficiency of airports. By applying this approach, policy makers and practitioners can effectively compare operational efficiency between airports, and therefore generate more informed decisions.

Keywords: Airport efficiency, Analytic Hierarchy Process (AHP), Data Envelopment Analysis (DEA), Assurance Region DEA (DEA-AR model).

1. Introduction

Airport efficiency evaluation has been a burgeoning area of research in recent years. These analyses are important for a variety of stakeholders, including airports, regulatory bodies, governments, passengers and airlines (Humphreys and Francis, 2002). Motivations for examining airport efficiency include assessing financial and operational efficiency, evaluating alternative investment strategies and monitoring airport activity (Doganis, 1992).

Lai et al. (2012) pointed out that after the year 2000, more than 50 papers related to airport efficiency have been published, but before this, only four papers were published. From a methodological perspective, one of the dominant approaches taken has been the application of econometric tools, featuring in 80% of all published papers in this area (Lai et al., 2012). In terms of the specific techniques adopted, Data Envelopment Analysis (DEA) featured in one of the first papers published (Gillen and Lall, 1997), and has become a popular tool since then, being employed in around 50% of these papers. In doing so, developments to improve accuracy with the employment of DEA, such as bootstrapping, have been incorporated (Curi et al., 2011).

In a DEA model, the preference weights of input and output variables are automatically calculated, but the importance of these variables relative to each other is not included in the calculation (Coelli et al., 2005). Therefore, it is considered that each variable has an equal level of importance. In reality, preference will be given towards certain variables and these preferences may change depending upon the considered stakeholders. For example, Humphreys and Francis (2002) discuss how airport managers, airport owners/shareholders, governments, airlines and passengers have varying motivations for performance measurement, and therefore use different measures.

To resolve this problem, applying a Multi-Criteria Decision Making (MCDM) method to derive the weight of importance of each variable, before undertaking DEA analysis, is a way of overcoming this issue. A popular method of MCDM is the Analytic Hierarchy Process (AHP). AHP develops from a linear additive model, respectively, on pairwise comparisons between criteria and between variables (Saaty, 1980). In the context of airport management, AHP has seen use in the context of evaluating the risk factors for a logistics hub development (Tsai and Su, 2002), evaluating the competitiveness of Asia-Pacific air cargo hubs (Chao and Yu, 2013) and choosing a simulation software package to support airport operations (Otamendi et al., 2008).

In this paper, AHP and DEA are combined to evaluate airport efficiency, an approach which has not previously been undertaken within published research in this area. Through this, the effectiveness of the DEA Assurance Region (DEA-AR) model as a means for increasing discriminatory power is highlighted, as an alternative to other approaches, such as changing the ratio of decision making units to variables (Charnes et al., 1985) or referral clustering (Zhu, 2009). A secondary aim of the paper is to show the value of combining AHP and DEA in reflecting the opinions of different stakeholder groups. While this combined approach has been adopted elsewhere, it has not been applied to the air transport sector. As identified earlier, the stakeholder groups may have different views on the importance of particular variables, which then influence their perception of efficiency (in airport terms).

The paper proceeds as follows. Section 2 examines the airport efficiency evaluation literature, while section 3 reviews AHP/DEA models. In section 4, elucidation of the AHP and DEA model employed in this analysis is given. The next section describes the collection of the data required in our analysis. In section 6, the AHP specific results are expounded, followed in section 7 with the DEA results (post use of AHP findings) being presented in terms of the two efficiency models considered. In section 8, discussion and conclusions are given, including thoughts towards future research.

2. Airport efficiency evaluation

In the mid-1990s, the literature on efficiency evaluation, which had already been applied to numerous industries, was introduced to the airport sector (Gillen and Lall, 1997). Since then, a number of papers have been published on airport efficiency, although the depth of coverage is perhaps less than in other transport industries such as seaports (Woo et al., 2011).

One approach adopted is the use of partial measures, which calculate the ratios of one input to one output to assess efficiency in relation to a specific dimension. Francis et al. (2002) highlighted that the denominator is often a Work Load Unit, defined as one passenger processed or 100 kg of freight handled. A further discussion of partial measures can be found in Graham (2005), while an application of this approach can be found in the UK Competition Commission's investigation into BAA plc (Competition Commission, 2008).

Another set of approaches is associated with MCDM, which establishes preferences between options against a specific set of objectives. The use of these approaches within airport efficiency literature is limited. For example, Wang et al. (2004) used Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate the operational efficiency of Taiwanese airports. While AHP is a popular MCDM approach, its use has been limited to other areas of airport management, including airport development (Vreeker et al., 2002; Zietsman and Vanderschuren, 2014), customer service (Correia et al., 2008; Tsai et al., 2011) and airport security (Yoo and Choi, 2006).

By far the most popular approach for efficiency evaluation has been the use of frontier analysis methods. These methods identify an efficient frontier and then evaluate inefficiency against this. DEA is the most prevalent of the associated methods; Lai et al. (2012) identified 23 papers using DEA between 1997 and 2011, including variants of DEA. Other frontier methods used to evaluate airport efficiency include the Total Factor Productivity index method (Hooper and Hensher, 1997), Stochastic Frontier Analysis (Oum et al., 2008; Barros, 2008), Variable Factor Productivity (Oum et al., 2012) and a Bayesian dynamic frontier model (Assaf et al., 2012).

Finally, combinations of approaches have been used in a limited number of papers (see Pels et al., 2001; Martin and Roman, 2006; Yang, 2010; Assaf and Gillen, 2012). These combinations have focused on bringing together different (objective) frontier analysis approaches. Papers that combine MCDM and efficiency evaluation have not yet been used in airport efficiency analysis, although they have been used in other transport and logistics applications. For example, Azadeh et al. (2008) combined AHP and DEA to find the optimal solution to improve railway timetable reliability and efficiency; Korpela et al. (2007) used the same combination of approaches in the context of warehouse management. Therefore, considering the combination of AHP and DEA in airport efficiency represents a research opportunity.

3. Integrated AHP/DEA models

Within the literature, Ho (2008) undertook an extensive review of integrated AHP and its applications, and has reported only a limited number of publications with combined AHP and DEA models. Several studies have indicated that AHP can be applied to form an AHP/DEA ranking model for the purpose of improving DEA usability (Feng et al., 2004; Friedman and Sinuany-Stern, 1998; Lee and Tseng, 2006; Sinuany-Stern et al., 2000). The advantage of the AHP/DEA ranking model is that the comparative weight (or importance) can be derived for inputs/outputs via an AHP pair-wise comparison (Lee and Tseng, 2006; Sinuany-Stern et al., 2000). Alternatively, Saen et al. (2005) proposed a combined AHP and DEA approach to measure the relative efficiency of slightly non-homogeneous decision making units.

While there are a number of advantages from AHP/DEA, Wang et al. (2008a) highlight some of the shortcomings. These include illogical or overestimated local weights, oversensitivity to some comparisons and information loss (Wang et al., 2008a). An alternative approach put forward in the literature is to use a DEA model with Assurance Region (DEA-AR; Thompson et al., 1986) instead. The Assurance Region allows weights to vary within a region by imposing constraints on the relative magnitudes of the weights for special items (Kong and Fu, 2012). Examples of where the combined AHP/DEA-AR model has been used include Seifert and Zhu (1998) and Takamura and Tone (2003).

In terms of applications, AHP/DEA models have been used for a number of purposes. Chen and Chen (2007) and Hsu (2005) use this integrated model with a Balanced Scorecard performance evaluation, both in the context of research and development projects. AHP is used to determine the importance of the different performance measures. Wang et al. (2008b) use an integrated model to evaluate risks in bridges, where the inclusion of DEA enables a greater number of structures to be evaluated.

A further area of use is in facility layout design and operation. Yang and Kuo (2003) proposed a combined AHP and DEA approach to solve a facility layout design problem. A computer-aided

layout planning tool was adopted to generate a number of alternative layouts in advance. The relative importance weightings of alternative layouts were obtained by using the AHP pair-wise comparison with respect to three qualitative factors: flexibility, accessibility, and maintenance. DEA was then used to solve the layout design problem by simultaneously considering both the qualitative and quantitative performance data leading to the identification of performance frontiers. A similar approach is used in Ertay et al. (2006). Meanwhile, Korpela et al. (2007) developed an approach to select a warehouse operator network by combining the AHP and DEA. The outcome of the AHP analysis was a preference priority for each alternative operator describing the expected performance level.

Finally, Takamura and Tone (2003) developed a combined AHP and DEA-AR approach to deal with the relocation of several government agencies out of Tokyo. Firstly, AHP was used to obtain the relative importance weightings of both criteria and attributes. Secondly, based on the AHP weightings, DEA-AR was adopted to measure the effectiveness of alternative locations.

4. Model elucidation

In this section, the model used within this paper is elucidated, starting with AHP before developing the DEA-AR and integrated models.

4.1. AHP

The first stage of the model is to conduct an AHP analysis to determine the relative weights of each of the input and output variables to be evaluated in the DEA-AR model. The AHP is aimed at integrating different measures into a single overall set of scores for ranking Decision Alternatives (DAs) (Önü and Soner, 2008). There are five main steps in the AHP (Saaty, 2008):

- (1) Define the decision object.
- (2) Classify the variables which affect the decision and build a multi-level structure. The top level is the goal of this decision, the intermediate levels are criteria and sub-criteria of comparing DAs, and the lowest level are alternatives DAs.
- (3) Make comparisons between each criterion in an upper level and the same criterion in its below level in terms of relative importance; that is, forge a set of pair-wise comparison decision matrices. Let Z represent an $n \times n$ pair-wise comparison matrix, which can be expressed as:

$$Z = [a_{fg}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}, \quad (1)$$

where $a_{ff} = 1$ and $a_{fg} = 1/a_{gf}$, $f, g = 1, 2, \dots, n$, and $a_{fg} > 0$.

Let C_1, C_2, \dots, C_n denote the set of criteria, while a_{fg} represents a quantified judgement on a pair of criteria C_f and C_g . In order to make a contrast about the degree to which one criterion is more important than another, the original 1-9 scale by Saaty (1980) is used. The values of 1, 3, 5, 7, and 9, in), represent equal importance, weak importance, essential importance, demonstrated importance, and extreme importance, respectively; while the values 2, 4, 6, and 8 are used to compromise between the above values.

- (4) To calculate the importance degree, the normalisation of the geometric mean method is used to determine the important degrees of the decision maker's requirements (Escobar et al., 2004). Let W_f denoted the importance degree (weight) for the f^{th} criteria, then:

$$W_f = \sqrt[n]{\prod_{g=1}^n a_{fg}} / \sum_{f=1}^n \sqrt[n]{\prod_{g=1}^n a_{fg}}, f, g = 1, 2, \dots, n \quad (2)$$

where n is the number of criteria.

In addition, the maximum eigenvalue λ_{\max} can be calculated by Equation (3) and Equation (4):

$$Z \times W_f = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \times \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} = \begin{bmatrix} W_1' \\ W_2' \\ \vdots \\ W_n' \end{bmatrix}, \quad (3)$$

$$\lambda_{\max} = (1/n) \times (W_1'/W_1 + W_2'/W_2 + \cdots + W_n'/W_n). \quad (4)$$

- (5) The final step is to test the matrix consistency through calculation, modifying it if necessary in order to get an acceptable consistency. In line with the premise of the consistency test, the associated eigenvector is calculated corresponding to the maximum eigenvalue λ_{\max} of the pair-wise comparison matrix. The Consistency Index (CI) can be calculated using λ_{\max} where n is the size of matrix:

$$CI = (\lambda_{\max} - n)/(n - 1). \quad (5)$$

From this, Saaty (1980) defined the consistency ratio (CR) as:

$$CR = CI / RI \quad (6)$$

Where RI is the average value for random matrices using the Saaty scale (Forman, 1990). A matrix is only accepted as consistent if $CR < 0.1$.

By following these five steps, the weight between each criterion is then determined.

Within the academic literature, there has been much debate on AHP including the questioning of a number of associated technical issues. While not specifically addressed in this study, the mention of such issues here will benefit the reader in what may be pertinent for future research, conferring in a policy context the reliability of results. These issues include the specific importance scale used, here the 1-9 scale, with others also considered pertinent and the sensitivity of results to the hierarchical structure adopted. associated references include Weber et al. (1988), Ma and Zheng (1991), Carmone Jr. et al. (1997), Pöyhönen et al. (1997), Beynon (2002), Kwiesielewicz and van Uden (2004) and Bana e Costa and Vansnick (2008).

4.2. DEA and DEA-AR

DEA is a popular mathematical programming methodology based on the efficiency frontier (Charnes et al., 1978). DEA is used to evaluate the relative efficiencies of DMUs which have multiple inputs and outputs (Chen, 2008). A DMU is considered relatively inefficient if its efficiency score is less than 1. The DEA-BCC (Banker-Charnes-Cooper) model is chosen in this research as the

airport sector often achieves variable returns to scale, due to imperfect competition, government regulations and financial constraints. In addition, an output orientation is going to be employed because once an airport investment has been made, such as the building of new terminals, it is very difficult for airport authorities to disinvest to save costs by amending their input variables, thereby invalidating the input orientation (Gillen and Lall, 1997; Oum et al., 2006).

The output-oriented BCC model evaluates the relative efficiency of n airports (DMU_k , $k = 1, 2, \dots, n$). Every DMU_k uses m inputs ($i = 1, 2, \dots, m$) and produces s outputs ($r = 1, 2, \dots, s$). The relative efficiency value of DMU_k can then be obtained as follows:

$$\begin{aligned} \text{Max } h_k &= \mathring{a} \sum_{r=1}^s u_r y_{rk} - u_a & (6) \\ \text{s.t. } \mathring{a} \sum_{i=1}^m v_i x_{ik} &= 1 \\ \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} - u_a &= 0, j = 1, \dots, n \\ u_r, v_i &\geq \varepsilon, i = 1, 2, \dots, m, r = 1, 2, \dots, s, \text{ and } u_a \text{ free in sign,} \end{aligned}$$

Where, h_k is the efficiency value of airport k ; y_{rj} is r^{th} outputs of the j^{th} DMU; x_{ij} is i^{th} inputs of the j^{th} DMU; u_r is a weight of r^{th} output of airport k and v_i is a weight of i^{th} input of airport k . Further, ε represents the extremely small positive number to make all u_r, v_i positive; u_a is equivalent to an intercept. From the above model, the optimal input/output multipliers can be determined.

As a development of the above model, Thompson et al. (1986) proposed the DEA-AR model. In a basic DEA model, an efficient DMU may weight a single input and a single output, with the other inputs and outputs being weighted zero (Kong and Fu, 2012). The DEA-AR model, however, can vary weights within a region by imposing constraints on the relative magnitudes of the weights for special items (Kong and Fu, 2012). For every pair of input and output measurements, lower (L) and upper (U) bounds for the ratio of weights are defined. These are defined as:

$$\begin{aligned} L_{i_1 i_2} &\leq (v_{i_1} / v_{i_2}) \leq U_{i_1 i_2} \\ L_{r_1 r_2} &\leq (u_{r_1} / u_{r_2}) \leq U_{r_1 r_2} \end{aligned} \quad (7)$$

Where v_{i_1}/v_{i_2} is the ratio of weights in the DEA model for a pair of inputs i_1 and i_2 , while u_{r_1}/u_{r_2} is the ratio of weights in the DEA model for a pair of outputs r_1 and r_2 . These constraints limit the regions of weights to a special area, which is the assurance region (AR), and represent additional constraints in equation (6). In the AHP/DEA-AR model, the L and U for each pairwise comparison are determined from the AHP results. The ratios of the AHP weights (W_{ij}) are calculated for every respondent, and the minimum and maximum values within these sets of ratios are then used to define L and U , respectively.

5. Data collection

The data collection process for this research followed two main stages. Firstly, variables for the model were selected, along with the sample of airports. Second, in order to enable the AHP

analysis, a questionnaire survey was carried out. Finally, DEA models were applied to airport data for 2010 (Air Transport Research Society, 2011)

5.1. Variable and sample selection

In determining the variable set to be used, reference was made to a number of previous papers that had analyzed the inputs and outputs used in air transport productivity analyses (Tovar and Martin-Cejas, 2010; Lai et al., 2012) and covering the range of techniques identified earlier. These studies highlighted a mix of variables used in relation to capacity, service and financial measures. Lai et al. (2012) provided a ranking of the top variables used, categorised according to their nature (such as financial). In considering which of these to adopt, consideration was given as to the availability of data, and the extent to which overlap existed between the variables. Further, it was observed that most studies took variables from one cluster of metrics, with only limited studies (such as Sarkis and Talluri, 2004; Oum et al., 2008; Assaf and Gillen, 2012) using a broader range. Therefore, the decision was taken to consider, for inputs, capacity and financial measures and, for outputs, service and financial measures.

A set of six input and four output measures were chosen based on these criteria. In Figure 1, an illustration of the hierarchical model necessary for the AHP analysis is shown, including the different criteria levels incorporated into this model. The inputs used in the variable set are:

- Number of Employees – the number of full time equivalent employees directly employed by the airport.
- Number of Gates – the number of gates through which aircraft can be loaded.
- Number of Runways – the number of available runways at each airport.
- Size of Terminal Area – the total area of passenger terminals.
- Length of Runway – the average runway length at the airport.
- Operational Expenditure – the financial resources needed to run an airport, including salaries and benefits, communications, supplies, materials and other expenses.

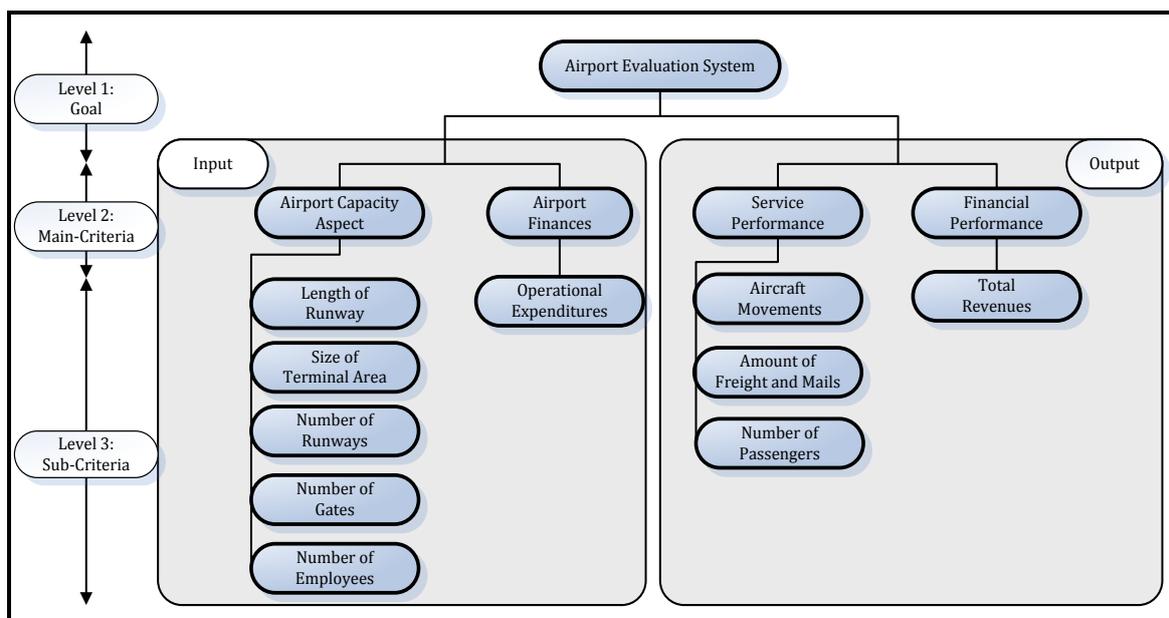


Figure 1: AHP hierarchies of variable set

The first five of these variables were considered to be capacity related, reflecting categorisations by Tovar and Martin-Cejas (2010) and others. Those related to infrastructure reflect the number of

flights and size of aircraft that an airport can handle. Some infrastructural aspects such as apron size are not included, although this reflects data availability and the need to limit the number of variables. The data does not take into account the configuration of the infrastructure either, such as if the runways cross each other, although this is consistent with other studies. The number of employees will be reflective of the volume of passengers and freight handled by the airport. However, this number will also be affected by decisions taken, for example, in respect of outsourcing of activities. Operational expenditure may also be affected by this, and also cost differences between the different countries within which the airports are based. While acknowledging these issues, such variables can still be considered consistent with managerial interests and other academic studies.

Four outputs were chosen (see also Figure 1), thus:

- Number of Passengers – the number of passengers arriving or departing by air at an airport, thereby including both terminal and transit passengers.
- Amount of Freight and Mail – the weight of cargo and mail handled at the airport.
- Aircraft Movements – the number of landings and take offs by aircraft engaged in transporting passengers, freight and mail.
- Total Revenues – covering both aeronautical and non-aeronautical revenues generated by the airport.

As with the considered input variables, these measures provided a balanced approach, reflecting the throughput at the airport as well as the financial benefits that this brings. Consideration was given to separating revenue into aeronautical and non-aeronautical revenues, but the availability of consistent data between the sample airports precluded this. Other measures of service were also considered (such as the use of the Skytrax (<http://www.airlinequality.com>) rating system for airports), but incomplete and incomparable data sets made this unfeasible.

Having done this, three pilot interviews were conducted to verify that the metrics were appropriate. These were with experts from both practice and academia and each had been involved in the air transport industry for more than 20 years. As well as providing them with the selected list, they were also shown the wider list from Lai et al. (2012). They provided the following comments on the variables chosen:

- Inputs: The experts agreed that the measures chosen were appropriate in both being able to influence the level of output and allowing comparisons between airports. In terms of financial measures, they concluded that operational expenditure was the most appropriate because non-operational expenditure may be distorted by significant capital investments. Of the excluded measures, their view was that these were less suited to evaluating efficiency or duplicated measures already included.
- Outputs: All of the experts felt that the philosophy of a business operation is to learn how to acquire maximum benefit by applying limited resources. The service variables reflect these benefits. For financial measures, total operating revenues was the most appropriate because of the increasing importance on non-aeronautical revenues.

The next stage was to choose a sample of airports to analyse. Charnes et al. (1985) highlights that, for DEA to be effective, the total number of DMUs must not exceed the product of the number of inputs and outputs. By contrast, Ali et al. (1987) and Bowlin (1987) both advise that the number of DMUs should be at least twice the sum of the input and output variables. In this study, the limit

set by Charnes et al. (1985) was the largest and so 24 airports were selected. In determining the sample, three main criteria were applied. First, it was decided to focus upon airports from Europe and the Asia-Pacific regions. Given these regions are at different stages of privatisation and commercialisation of their airport infrastructure (Yang et al., 2008; Ison et al., 2011; Assaf and Gillen, 2012; Gong et al., 2012), it was thought that there may be differences in efficiency, and therefore more opportunity of discrimination between airports in the results. Second, the sample should cover most of types of airport ownership, as put forward by Gillen (2011). Finally, the sample airports should be similar in nature and operations, as derived from the limitations of DEA, and so the sample airports consisted only of primary airports in the two previously selected regions. This final criterion was determined by the annual number of passengers, as detailed in Airport Council International (2011). Details of the 24 airports can be found in Table 1.

Table 1: Sample airports in this research

Europe	Ownership Category	Asia-Pacific	Ownership Category
Amsterdam (AMS)	Private company (Public majority)	Bangkok (BKK)	Private company
Barcelona (BCN)	Public-owned company	Beijing (PEK)	Private company
Frankfurt (FRA)	Private company (Public majority)	Guangzhou (CAN)	Private company
Istanbul (IST)	Public-owned, operated by a private company	Hong Kong (HKG)	Public-owned company
London (LGW)	Private company	Incheon (ICN)	Public-owned company
London (LHR)	Private company	Kuala Lumpur (KUL)	Public-owned company
Madrid (MAD)	Public-owned company	Osaka (KIX)	Private company (Public majority)
Munich (MUC)	Public-owned company	Tokyo (HRT)	Public-owned company
Paris (CDG)	Private company	Shanghai (PVG)	Public-owned company
Paris (ORY)	Private company	Singapore (SIN)	Public-owned
Rome (FCO)	Private company	Shenzhen (SZX)	Private company (Public majority)
Zurich (ZRH)	Private company	Sydney (SYD)	Private company

The panel data of input and output variables of this paper were applied to 2010 data and were taken from the Air Transport Research Society (ATRS) 2011 benchmarking report. The descriptive statistics of inputs and outputs variables selected in the paper are provided in Table 2. In the source data, all financial values are quoted in US dollars and therefore we assume that this adjusts for any currency variations, reflecting the approach of similar studies with the same data (Oum et al., 2012).

In addition, when measuring the efficiency and technology gaps existing in airports, most studies have used revenue as the output variable (e.g. Hooper and Hensher, 1997; Oum et al., 2006, 2008;

Tovar and Martin-Cejas, 2010). The revenues of an airport indicate the operating scales and strengths of airport, and all airports must have sufficient amounts of revenue to maintain the operation of their services. Hence, this study uses Total Revenues as an output variable and Operational Expenditure as input.

Table 2: Descriptive statistics of input and output variables

Variables	Minimum	Maximum	Mean	S.D.
Input				
Number of Employees	306	17,996	3,170	3,688
Number of Gates	32	264	104	49
Number of Runways	1	6	3	1
Size of Terminal Area (m ²)	152,000	1,382,000	504,551	302,793
Length of Runway (ft)	2,850	4,090	3,534	374
Operational Expenditure (\$ millions)	95	1,851	607	480
Output				
Number of Passengers (000's)	16,014	67,056	36,929	13,573
Amount of Freight and Mails (tons)	104,239	3,400,000	1,096,956	930,970
Aircraft Movements	133,502	559,812	315,314	115,546
Total Revenues (\$ millions)	217	2892	982	656

Before conducting the efficiency analysis, a correlation coefficients analysis is applied to determine the relations between the input and output variables. Table 3 presents all of the relationships between each input and output variable. The results show that all of the variables can satisfy the isotonicity test property, which means that an output should not decrease with an increased input. All of the correlation coefficients are positive. Therefore, all of the different resources and facilities are generally dimensioned jointly to avoid conflict.

Table 3: Correlation coefficients among input and output variables

Output Variables	Input Variables					
	Number of Employees	Number of Gates	Number of Runways	Size of Terminal Area	Length of Runway	Operational Expenditures
Number of passengers	0.340	0.632**	0.280	0.312	0.281	0.662**
Amount of freight and mail	0.230	0.190	0.070	0.532**	0.313	0.297
Aircraft movements	0.452*	0.584**	0.480*	0.135	0.187	0.640**
Total Revenue	0.439*	0.725**	0.145	0.181	0.233	0.932**

**Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Further, a Mann-Whitney U test was carried out to identify if there were statistically different rankings in the efficiency evaluations due to geography or ownership (public/private). U Values from the test of 66 and 54 were achieved for the DEA-BCC and AHP/DEA-AR results respectively. With 12 airports in each sample, the critical value of U is 37 (95% significance level) and therefore it can be concluded that any difference between the regions is due to chance. Comparative studies between regions are few, an exception being Vasigh and Gorjidoz (2006) who compare US and European airports. However, privatisation has tended to occur on a global basis – Graham (2011) highlights a first wave during the 1990s featuring almost every continent of the world – this lack of a regional difference could be expected. For ownership, U values of 126 (DEA-BCC) and 104 (AHP/DEA-AR) were achieved and, with the critical value of U at 95% significance being 36 (due to 14 public and 10 private owner airports), any difference between ownership groups is also due to chance. In this instance, the result reflects the findings of some studies in the literature (such as Oum and Yu, 2004; Lin and Hong, 2006; Vasigh and Gorjidoz, 2006), although other studies (for example, Pels et al., 2001; Oum et al., 2008) suggest private ownership does improve efficiency.

5.2. AHP questionnaire

In order to discern the importance of the different input and output variables considered, a questionnaire was devised based on the hierarchy of measures in Figure 1. For Level 2, categories of capacity and finance for inputs, and service and finance for outputs were detailed. For Level 3, each of the individual variables identified were evaluated. Respondents were given a definition of each category/variable and asked to conduct pairwise comparisons on a 1-9 scale with ratings from equal importance to extreme importance (reflecting Saaty, 2008). In total, 15 different pairwise comparisons were contained in the questionnaire, along with brief demographic information about the respondent.

Two different respondent samples were sent the AHP questionnaires, to ensure that the secondary aim of the research (to determine the impact of different opinions on efficiency evaluations) could be met. The first sample was the managing directors of the 24 airport companies being considered in the efficiency analysis process. A further sample of 11 academic scholars from Europe, Asia and North America were sent questionnaires, as selected from an experts list provided by the Air Transport Research Society (ATRS). For both of these, it was expected that the respondent's perceptions would be consistent within each group.

Other stakeholders considered included airlines, passengers and policy makers. As previous research has shown, different types of airlines have varying requirements from airports (Warnock-Smith and Potter, 2005) and this may affect their perceptions. For passengers, their understanding of airport management may be limited, and so compromise their ability to effectively rank the variables chosen for this study. Finally, in terms of policy makers, difficulties in identifying appropriate personnel to send the survey to were encountered. This raised concerns that the response rate for these stakeholders may be lower.

Of the 35 questionnaires sent out, 25 completed questionnaires were returned, with a response rate 71.43%. The weight given by every respondent for each variable was calculated using the AHP process. The reliability of the weights was considered acceptable if the $CR < 0.1$. Where the CR was not considered acceptable, the questionnaires were excluded from the effective responses. In this study, three completed questionnaires had a $CR \geq 0.1$ and were removed, giving an effective response rate of 62.86% for 22 acceptable copies (see Table 4). In terms of geography, there were differences in the regional response rates for academia but not for practitioners. However, the result of this was an even split between academia and practice if considering Asian and non-Asian responses. Therefore, any impact on the findings should be negligible.

Table 4: Summary of AHP questionnaire response rate

	Sent out	Questionnaires returned	Response rate	Questionnaires with $CR < 0.1$	Response rate
Academic	11	8	72.73%	7	63.64%
Practice	24	17	70.83%	15	62.50%
Total	35	25	71.43%	22	62.86%

Having completed the data collection outlined, the information was then included within the model detailed in section 4. The results from this modelling are now presented, with the AHP outcomes in section 6 and the AHP/DEA-AR results contained in section 7.

6. AHP Results

Table 5 gives an overview of the AHP results generated from the survey, for inputs and outputs and Levels 2 and 3 (see Figure 1). Considering the inputs first, at Level 2, the experts considered financial inputs to be more important than capacity inputs. At Level 3, there were some variations between the capacity variables, with number of gates, size of terminal area and number of runways being considered the most important. These variables particularly reflect the number of aircraft an airport can handle, which then has an impact on financial inputs in relation to passenger and landing charges.

In terms of outputs, there was little difference in the prioritisation between the two categories at Level 2. However, differences exist at Level 3 for service measures, with passenger numbers being the most important. In the research, the focus has been on major passenger airports and therefore this finding may be a reflection of the sample of respondents to the survey. Movements are considered the least important, which is perhaps reflective of the revenue split between passenger based charges and aircraft based charges, particularly for large aircraft. As a simplified example, the landing fees from April 2013 for an airliner at London Heathrow Airport is a maximum of £1,563, while passenger fees are between £21 and £40 per departing passenger.

Therefore, a flight only needs to have 40 to 75 passengers on board before this revenue stream is greater than the landing fees (Heathrow Airport, 2013).

Table 5: AHP results for airport efficiency measures

	Level 2 category	Local weight	Level 3 variable	Local weight	Weight with respect to category
Input	Airport capacity	0.3759	No. of employees	0.0606	0.0228
			No. of gates	0.3122	0.1173
			No. of runways	0.2299	0.0864
			Size of terminal area	0.2516	0.0946
			Length of runway	0.1457	0.0547
	Financial measures	0.6241	Operating expenditure	0.6241	0.6241
Output	Service	0.5005	No. of passengers	0.5206	0.2605
			Amount of freight and mail	0.3296	0.1649
			No. of aircraft movements	0.1498	0.0750
	Financial measures	0.4995	Total revenue	0.4995	0.4995

A sensitivity analysis has been carried out, increasing the priority weights for randomly selected variables and, having recalculated the AHP values, observing any changes in the priority order of the inputs and outputs. Number of employees and amount of freight and mail had their priority weights doubled, but the rank order of the remaining variables remained constant.

The results derived from the AHP analysis then served as a guideline for setting the upper and lower bounds in the AHP/DEA-AR model. To do this, the AHP results for each respondent were used (Table 6), with pair-wise divisions between all of the weights made. Weights W_1 to W_6 are input variables in the DEA model while W_7 to W_{10} are the output variables. The largest and smallest values of each weight ratio for all respondents are then found and the upper and lower bounds values of this weight ratio are then constructed. For example, for Respondent 11 (in Table 6) the ratio W_1/W_2 takes on a value of $0.0646/0.0238 = 2.7143$. The ratio W_1/W_2 for the other 21 respondents can be calculated in the same way. Therefore, the highest $W_1/W_2 = 2.7143$ from Respondent 11 is used as the upper bound of the ratio W_1/W_2 , and the smallest W_1/W_2 is 0.0765 from Respondent 2, which is used as the lower bound. Other ranges (or upper and lower bounds) of ratio weights can be found in Table 7.

Table 6: AHP weights of input and output variables of respondents

Variables	Input Variables					Output Variables				
	Number of Employees	Number of Gates	Number of Runways	Size of Terminal Area	Length of Runway	Operational Expenditure	Number of Passengers	Amount of Freight and Mails	Aircraft Movements	Total Revenues
Respondent	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}
1	0.0113	0.0697	0.0661	0.0755	0.0275	0.7500	0.0632	0.0505	0.0113	0.875
2	0.0046	0.0601	0.0252	0.0382	0.0148	0.8571	0.1118	0.0704	0.0177	0.8000
3	0.0205	0.2157	0.0990	0.1368	0.0281	0.5000	0.0667	0.0667	0.0095	0.8571
4	0.0103	0.0952	0.0389	0.0899	0.0158	0.7500	0.2222	0.2222	0.0556	0.5000
5	0.0056	0.0627	0.0302	0.0543	0.0139	0.8333	0.2273	0.2273	0.0455	0.5000
6	0.0063	0.0641	0.0288	0.0518	0.0157	0.8333	0.0857	0.0857	0.0286	0.8000
7	0.0058	0.0669	0.0242	0.0148	0.0551	0.8333	0.1062	0.043	0.0175	0.8333
8	0.0308	0.1803	0.2993	0.2303	0.0925	0.1667	0.3815	0.3468	0.1050	0.1667
9	0.0318	0.2050	0.0744	0.3522	0.1699	0.1667	0.0912	0.0574	0.0181	0.8333
10	0.0050	0.0385	0.0329	0.0531	0.0133	0.8571	0.6086	0.2004	0.066	0.1250
11	0.0646	0.0238	0.0155	0.0201	0.0189	0.8571	0.0416	0.0262	0.1322	0.8000
12	0.0332	0.0189	0.1016	0.0125	0.0337	0.8000	0.3304	0.1041	0.0656	0.5000
13	0.0257	0.3525	0.1152	0.0769	0.2297	0.2000	0.3185	0.1291	0.0524	0.5000
14	0.0269	0.2047	0.4294	0.0558	0.1164	0.1667	0.3694	0.141	0.3229	0.1667
15	0.0129	0.0785	0.0371	0.0345	0.0371	0.8000	0.4405	0.1388	0.0874	0.3333
16	0.1898	0.1421	0.2201	0.1604	0.1209	0.1667	0.0781	0.3293	0.0926	0.5000
17	0.0067	0.0538	0.0226	0.0592	0.0244	0.8333	0.3704	0.3704	0.0926	0.1667
18	0.0179	0.1004	0.0823	0.2445	0.0549	0.5000	0.5269	0.2102	0.0629	0.2000
19	0.0099	0.0577	0.0757	0.0790	0.0277	0.7500	0.3030	0.3030	0.0606	0.3333
20	0.0134	0.1041	0.0284	0.0839	0.0202	0.7500	0.4700	0.0702	0.2098	0.2500
21	0.0310	0.1641	0.314	0.1525	0.1717	0.1667	0.3467	0.3815	0.1050	0.1667
22	0.0207	0.0392	0.0675	0.0198	0.0195	0.8333	0.1071	0.0357	0.1071	0.7500

Table 7: Upper and lower bounds of variables weight ratios

Input Weight Ratio	Upper	Lower	Output Weight Ratio	Upper	Lower
W_1/W_2	2.7143	0.0765	W_7/W_8	6.6952	0.2372
W_1/W_3	4.1677	0.0626	W_7/W_9	9.2212	0.3147
W_1/W_4	3.2139	0.0732	W_7/W_{10}	4.8688	0.0722
W_1/W_5	3.4180	0.1053	W_8/W_9	7.0211	0.3333
W_1/W_6	1.1386	0.0054	W_8/W_{10}	2.2885	0.0476
W_2/W_3	3.6655	0.4767	W_9/W_{10}	1.9370	0.0111
W_2/W_4	4.5839	0.4106			
W_2/W_5	7.6762	0.5608			
W_2/W_6	1.7625	0.0236			
W_3/W_4	8.1280	0.2112			
W_3/W_5	3.6890	0.4392			
W_3/W_6	2.5759	0.0181			
W_4/W_5	5.6899	0.2686			
W_4/W_6	2.1128	0.0156			
W_5/W_6	1.1485	0.0173			

These upper and lower bounds were then used within the DEA-AR model to generate efficiency scores for each of the 24 sample airports, as described earlier in section 4. These results were compared against those from a DEA-BCC model, to provide insights into the value of this alternative efficiency evaluation approach.

7. AHP/DEA-AR results

The results of the two efficiency models are summarised in Table 8. With the DEA-BCC model, 19 of the 24 airports are considered relatively efficient but with AHP/DEA-AR this reduces to just 5 airports. This is reflected in the average efficiency scores for the sample as a whole, which is 0.9719 for DEA-BCC and 0.7231 for AHP/DEA-AR. Consequently, there is greater discriminatory power within the latter model, as evidenced further by the standard deviation of the results increasing from 0.0786 to 0.2141. This discriminatory power is introduced through the DEA-AR model. This allows a distinction to be made between the remaining airports, increasing the value for practitioners and policy makers.

Table 8: Comparison of efficiency scores under DEA-BCC and AHP/DEA-AR

Airports	DEA-BCC		AHP/DEA-AR	
	Efficiency Score	Ranking	Efficiency Score	Ranking
1. Amsterdam	1	1	0.7589	11
2. Bangkok	1	1	0.6436	15
3. Barcelona	1	1	0.9088	6
4. Beijing	1	1	0.6579	14
5. Frankfurt	1	1	0.8574	8
6. Guangzhou	1	1	0.7168	13
7. Hong Kong	1	1	1	1
8. Istanbul	1	1	0.7360	12
9. Kuala Lumpur	0.9418	21	0.4379	22
10. London Gatwick	1	1	0.6167	17
11. London Heathrow	1	1	1	1
12. Madrid	1	1	0.8645	7
13. Munich	1	1	0.4965	21
14. Osaka	0.8975	22	0.5923	19
15. Paris Charles de Galle	1	1	1	1
16. Paris Orly	0.6551	24	0.3541	23
17. Rome Fiumicino	0.9983	20	0.6094	18
18. Seoul Incheon	1	1	0.8531	9
19. Shanghai Pudong	1	1	0.7907	10
20. Shenzhen	1	1	1	1
21. Singapore	0.8318	23	0.2471	24
22. Sydney	1	1	0.5793	20
23. Tokyo Narita	1	1	0.6343	16
24. Zurich	1	1	1	1
Mean of all samples	0.9719		0.7231	
Standard Deviation	0.0786		0.2141	

Another benefit of using the DEA-AR model is to avoid extreme weight distribution. The weight distributions of output variables for the DEA models are shown in Table 9. Because the output oriented DEA model is applied in this research, only the distribution of output variables needs to be discussed (Cooper et al., 2006). For the DEA-BCC model, there are many zero weights for the selected output variables, which is unreasonable when evaluating an airport's efficiency relative to its peers. This situation is not found to exist in the DEA-AR model, in which all of the output weights are larger than zero. That implies when using DEA-AR model to assess airport efficiency, all the output variables are considered if comparing the weight distribution of variables with the integrated DEA-BCC model.

Table 9: The weight distribution of output variables

Airports ^a	DEA-BCC model				AHP/DEA-AR model			
	W_7	W_8	W_9	W_{10}	W_7	W_8	W_9	W_{10}
1	0.0498	0.2374	0.7129	0	0.0974	0.4810	0.4112	0.0103
2	1	0	0	0	0.1591	0.0820	0.7586	0.0004
3	0	0.1733	0.3918	0.4349	0.0902	0.5317	0.3671	0.0111
4	1	0	0	0	0.1236	0.4956	0.3806	0.0003
5	1	0	0	0	0.1991	0.0977	0.6876	0.0156
6	1	0	0	0	0.1253	0.7766	0.0970	0.0011
7	1	0	0	0	0.1637	0.1582	0.6777	0.0005
8	0	0	1	0	0.1263	0.1499	0.7081	0.0157
9	0	0	0.9883	0.0117	0.1029	0.5503	0.3463	0.0006
10	0.0409	0	0.3498	0.6093	0.1736	0.1385	0.6831	0.0048
11	0.0944	0	0.5061	0.3995	0.1667	0.0971	0.7351	0.0010
12	0.5510	0.3119	0.1371	0	0.1166	0.3054	0.5771	0.0009
13	1	0	0	0	0.1347	0.5539	0.3109	0.0004
14	1	0	0	0	0.1235	0.4511	0.4251	0.0003
15	0.5782	0	0.4218	0	0.1278	0.3916	0.4803	0.0003
16	1	0	0	0	0.0284	0.9523	0.0191	0.0001
17	0	0.3560	0	0.6440	0.0029	0.9836	0.0122	0.0013
18	1	0	0	0	0.1358	0.4988	0.3651	0.0003
19	0	0	0.0114	0.9886	0.0250	0.8708	0.0835	0.0207
20	0	0	0.5303	0.4697	0.0744	0.7150	0.1975	0.0131
21	0.4175	0.5825	0	0	0.0078	0.7594	0.2326	0.0002
22	0	0	0	1	0.1339	0.3633	0.4859	0.0169
23	1	0	0	0	0.0590	0.7348	0.2061	0.0001
24	1	0	0	0	0.1383	0.2952	0.5633	0.0032

^a Airport index relates to airports presented in Table 6

Returning to the specific airport results in Table 8, in relation to the ranking of airports those with the lowest rankings are consistent between the two models. In terms of characteristics, they are also airports with lower passenger numbers within the airport sample. Their low efficiency ranking may therefore relate to the perception of the importance of passenger numbers from the AHP results. However, it is important to look beyond the numbers to consider why they are considered inefficient. Taking the example of Singapore (airport 21), the airport only achieved an efficiency score of 0.2471 with the AHP/DEA-AR model. An explanation is that Singapore airport has the second largest size of terminal area (1,043,020m²) but its output efficiency is much lower, being ranked 21st for number of passengers, 17th for amount of freight, 23rd for aircraft movements, and 11th for total revenues. Potential root causes for the efficiency score include management efficiency objectives that place a greater emphasis on passenger experience and the introduction of additional terminal capacity. Consequently, although in the short term Singapore airport is under-utilised, it allows for passenger number growth in the long term.

Finally, as part of the analysis, consideration was given as to the potential for the distinguishing between different groups of stakeholders in their perception of airport efficiency. As noted in the method, the surveys were received from both academics and practitioners. Therefore, new AHP scores were calculated for each of these groups and the DEA-AR model recalculated from these.

While the local weights for the Level 3 variables were similar between the groups, more substantial differences at Level 2 were observed. For the inputs, practitioners weighted the financial aspects more important than capacity (0.6450 versus 0.3549) whereas academics had only a slight bias towards financial aspects (0.5245). Practitioners were also slightly biased towards financial outputs (0.5867) while academics placed a substantial weight on the service related measures (0.7349). This highlights a difference in perspective between these groups, which also has some impact on the DEA-AR results, as can be seen in Table 10. Therefore, the research highlights that, in making efficiency judgements, perceptions of efficiency will change depending upon who is considering the results.

Table 10: Comparison of efficiency rankings for academic and practice perspectives using AHP/DEA-AR model

Airports	Academia		Practice	
	Efficiency Score	Ranking	Efficiency Score	Ranking
1. Amsterdam	0.6204	10	0.7552	11
2. Bangkok	0.5354	14	0.6314	16
3. Barcelona	0.4217	17	0.8799	6
4. Beijing	0.4622	15	0.6373	14
5. Frankfurt	0.6780	8	0.8470	8
6. Guangzhou	0.5510	13	0.7116	13
7. Hong Kong	1	1	1	1
8. Istanbul	0.5981	11	0.7282	12
9. Kuala Lumpur	0.3385	19	0.4311	22
10. London Gatwick	0.3178	20	0.5866	19
11. London Heathrow	1	1	1	1
12. Madrid	0.4336	16	0.8331	9
13. Munich	0.2376	22	0.4940	21
14. Osaka	0.5749	12	0.5868	18
15. Paris Charles de Galle	0.8739	5	1	1
16. Paris Orly	0.1652	23	0.3418	23
17. Rome Fiumicino	0.2667	21	0.5936	17
18. Seoul Incheon	0.8478	6	0.8500	7
19. Shanghai Pudong	0.7633	7	0.7860	10
20. Shenzhen	1	1	1	1
21. Singapore	0.1545	24	0.2379	24
22. Sydney	0.3577	18	0.5666	20
23. Tokyo Narita	0.6271	9	0.6323	15
24. Zurich	1	1	1	1

In all cases, the efficiency values for airports increased for the practitioner perspective, suggesting that airport management has a particular focus upon financial management of their operations. However, the rankings between the airports are generally similar. The only significant differences are for Barcelona, Madrid, Osaka and Tokyo. For the Spanish airports, it appears that their operating costs in relation to the level of output is more in line with Asian airports than those in Europe, and so they perform better from a practitioners perspective. By contrast, the Japanese

airports in Osaka and Tokyo benefit from an academics perspective because of the volume of cargo they handle.

8. Discussion and conclusion

The main aim of this paper was to evaluate the impact of integrating AHP into DEA analysis in the context of airport efficiency. As noted earlier, while this has been undertaken in other sectors, it has yet to transfer into the transportation industry. Such a move is important as it enables the efficiency analysis to more accurately reflect the perceptions of stakeholders in relation to the selected variables. The study shows that, through using an AHP/DEA-AR model, that the subjectivity does affect the efficiency scores while adopting DEA-AR increases the discriminatory power of the analysis. This makes it easier to provide a ranking of airports and therefore compare one against the other.

A secondary aim was to use the approach to compare the efficiency scores for different groups of stakeholders. In this research, these groups were airport managers and academics. The AHP results highlighted quite significant differences between the perceptions of these two groups as to the importance of the different metrics. This in itself is an interesting finding, and perhaps raises the question as to whether we are fully considering the most appropriate metrics when evaluating airport efficiency (either quantitatively or qualitatively). However, because this was not the focus of the research, a detailed reasoning behind this cannot be identified.

When the AHP scores for the two groups are combined with the DEA-AR model, it can be seen that there are changes in the rankings for airports. For many, these changes are only slight (plus/minus two or three places), there are some airports with a more significant change. This is important to note as, more generally, while one group of stakeholders may consider an airport to be performing poorly, another group may consider its efficiency to be acceptable. It would be interesting in future research to develop this line of analysis further, considering a wider range of stakeholder groups (for example, policy makers, passengers) and possibly also geography (such as Europe, North America, Asia).

Overall, it can be concluded that bringing in subjective judgements through the AHP approach does provide new insights into airport efficiency and offers an opportunity for researchers in this area to develop results that are reflective of these perceptions. Such results will be able to contribute not only to benchmarking exercises but also the debates around issues such as privatisation, capturing different viewpoints and examining whether this influences overall rankings of airports.

Both policy makers and practitioners make decisions based upon comparisons with other airports, such as through the regulation of airports or by benchmarking against best practice. The AHP/DEA-AR approach developed in this paper allows a clearer definition of ranking scales, due to the differentiation, while also allowing measures to be prioritised depending upon the perspective of who is undertaking the comparison. For policy makers, it may be that decisions are influenced by a variety of stakeholders. Therefore, multiple comparisons using the same panel data but different stakeholder opinions may bring greater insight.

The research also offers a number of insights into potential future research opportunities. This paper combines AHP and the DEA-AR model. There are alternative approaches for both MCDM and efficiency analysis, and comparing combinations of these to AHP/DEA based approaches could give interesting insights. With respect to AHP, there are a number of technical issues often

debated in terms of what is good practice; a sample of these is discussed at the end of section 4.1. For example, in terms of the AHP 1-9 scale adopted, it has been argued that a linear approach is not reflective of human judgements and alternative scales have been developed (Beynon, 2002). The extent to which these would impact upon efficiency scores and rankings is unknown at this time, but could form a pertinent subject for future research. Further, there may be the opportunity to develop alternative hierarchies (or more layers) of input and output variables, which may enable more detailed insights into particular aspects of airport management to be considered. Finally, in terms of the stakeholder populations, as highlighted earlier there are a range of groups related to airports, such as policy makers, passengers and airlines. Obtaining AHP weights for these groups and comparing their efficiency scores with the results in this paper could offer further insights. This may also require an adjustment in the variables considered, to reflect the knowledge of the stakeholders being questioned.

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