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Andrius Jaržemskis and Ilona Jaržemskienė

Logistics and Transport management Department, Vilnius Gediminas Technical University, Vilnius, Lithuania

ABSTRACT

In order to compare the productivity of airports different scientific approaches are used by various authors. Previous research has shown wide application of the data envelopment analysis (D.E.A.) model for productivity comparison. The D.E.A. model may be used to compare both partial and total factor productivity. However, aggregation of the separate partial factors into a single D.E.A. model is still not sufficiently investigated. The purpose of this paper is to suggest the integration of two methods – DEA and Delphi Expert Panel – to solve this problem. A model was developed and experimentally tested with 15 major European Union airports. The results show that the suggested model could be efficiently used to compare the airports' productivity, which is expressed by a large set of attributes. The main conclusion is that model can be successfully used to compare airports by different criteria through integrating the DEA and Delphi Expert Panel techniques. The model can be used for any set of airports to compare productivity. The research could be useful to airport managers and investors, as well as to researchers in the area of D.E.A. application.

1. Introduction

Competition in air transport is becoming more acute as a result of the abolition of state regulation of the market (Truman & de Graaff, 2007). Airports are forced to increase the productivity of their existing infrastructure in order to remain competitive (Barros & Dieke, 2008). With the increasing number of flights, airports must develop their infrastructure to meet the growing needs of the market, but financial resources are limited so not all airports will be developed. The total comparative airport productivity (T.C.A.P.) is an important factor in attracting investors, whether an investment bank or the government, or a company, or a private investor. However, productivity is not a unified concept in the airport community (Bazargan & Vasigh, 2003). Currently, such a complex model of total productivity proposed by the authors of the article does not exist, and decisions on the improvement of technical parameters are made without evaluating the complex effect on airport productivity, instead

CONTACT Andrius Jaržemskis ✉ andrius.jarzemskis@vgtu.lt

assessing only the future benefits of specific improved technical parameters, such as an extended runway or expanded passenger waiting rooms.

The issue examined in the article is acute in the context of the European Union and global air transport organisations. The Advisory Council of Aviation Research and Innovation in Europe (A.C.A.R.E.) has developed an air transport vision for 2020 and has identified the most important research directions (Truman & de Graaff, 2007). One of the main directions is increasing airport productivity while reducing the negative environmental impact, reducing the prices for airport services and shortening the passenger, cargo and aircraft service time.

The International Civil Aviation Organisation (I.C.A.O.) considers the problem of infrastructure efficiency to be among the most important directions for their activities, because airport productivity becomes significant with the increase of airport load (ICAO, 2015). The International Air Transport Association (I.A.T.A.) has established a working group 'Airports and Navigation', one of the most important tasks of which is the measurability and increase of airport productivity. Airport productivity is also an objective relevant to the transport themes of the European Commission's Seventh Framework Programme for Research as well as Horizon 2020.

This article is relevant in terms of practical applicability of developed theoretical models. Airports with non-productive performance will no longer be dependent on the state and will eventually collapse. Airport productivity is measured as the ratio between the input and output. Comparison of airport productivity indicators with those of other major airports is significant for the airport management in the planning and management of airport operations and monitoring of performance.

This article presents work which aims to create and experimentally test an assessment model of the T.C.A.P. according to partial indicators, which would be applicable in practice to any range of airports, and which can be used to determine how a change in one of the technical parameters may affect the productivity of a range of airports under investigation. The data envelopment analysis (D.E.A.) method is used as background for T.C.A.P. model formulation.

The D.E.A. model may be used to compare both partial and total factor productivity. However, aggregation of the separate partial factors into a single D.E.A. model has still not been sufficiently investigated. The purpose of this paper is to suggest the integration of two methods – D.E.A. and Delphi Expert Panel – to solve this problem.

The paper is structured as follows. First, section 2 describes the literature and previous research on D.E.A. application. Section 3 gives a theoretical introduction to the model and proposed combination of D.E.A. and Delphi Expert Panel methods. The results of the empirical research are presented in section 4. Finally, section 5 summarises the conclusions made.

2. Literature review

The theoretical aspects related to the application of the systemic data analysis method are addressed in the works of Amirteimoori and Emrouznejad (2012), Angiz, Mustafa, and Emrouznejad (2010), Barros and Dieke (2008), Bian and Yang (2010), Chen (2009) and Cook, Yang, and Zhu (2009). A wide set of D.E.A. interpretations is summarised in the works of Cooper, Seiford, and Zhu (2004).

The Monte-Carlo method for relative productivity estimation was applied by Giraleas, Emrouznejad, and Thanassoulis (2012) similar to Khalili, Camanho, Silva Portela, and Alirezaee (2010). Improving envelopment in D.E.A. under variable returns to scale is presented by Thanassoulis, Kortelainen, and Allen (2012).

D.E.A. is a relatively new 'data oriented' approach for evaluating performance not only in air transport infrastructure but also in airline performance (Merkert & Hensher, 2011).

The productivity of airport performance is usually expressed as the ratio of input and output. The present section provides an analysis of limitations characteristic to the previous works and studies carried out on the subject of terminal productivity indicators. The findings of the previous research effort in the light of the latest developments within D.E.A. applications in transport were presented in Jarzemskiene's article (Jaržemskienė, 2009). Meta-analysis of DEA applications was carried also out by Odeck and Brathen (Odeck & Bråthen, 2012).

Efficiency analyses focus on the efficiency of some production process in transforming inputs into outputs. Frontier methods use an efficient frontier to identify the efficiency of individual organisations relative to a reference set of organisations. D.E.A. is a non-parametric approach that uses mathematical programming to identify the efficient frontier. Stochastic Frontier Analysis (S.F.A.) is a parametric approach that hypothesises a functional form and uses the data to econometrically estimate the parameters of that function using the entire set of Decision Making Units (DMUs). Both methods are widely used in research. It is clear that only S.F.A. can separate random noise from efficiency; D.E.A. incorporates noise as part of the efficiency score (Cordeiro, Sarkis, Vazquez, & Dijkshoorn, 2008). When comparing thousands of similar organisations, for example small and medium-sized enterprises, the elimination of so-called noise or marginal measures is worthwhile; however, when comparing very expensive large infrastructure units such as airports the marginal measures are required for better benchmarking. S.F.A. is more averages oriented compared with D.E.A.

Having examined best-practice examples, Graham (2003) and Francis, Humphreys, and Fry (2002) attempted to identify the performance indicators to be used for comparing the performance of different airports. A number of previous research papers analysed airport productivity using D.E.A. or similar models: in Australia (Abbott & Wu, 2002), in the U.S.A. (Bazargan & Vasigh, 2003), in Spain (Martin & Roman, 2001), (Martin-Cejas; 2002), in Brazil (Fernandes & Pacheco, 2005) and in Japan (Yoshida & Fujimoto, 2004). Some authors take a wider than national view. Continental research covers European (Pels, Nijkamp, & Rietveld, 2001) and Asia-Pacific (Lam, Low, & Tang, 2009) cases, or even international cases (Oum, Yu, & Fu, 2002).

The D.E.A. model may be used to compare both partial and total factor productivity. As noted by many authors, the scientific challenge here is in aggregation of the separate partial factors into a single D.E.A. model. The issue is highlighted in Pathomsiri, Haghani, Dresner, & R. J. (2006), and Zhu (2009). The challenge comes in evaluating productivity while attempting (1) to assign weight to each indicator and (2) determine the functional dependence between the respective indicators defining inputs and output. For instance, Nyshadham & Rao argued that in determining the weight of evaluation indicators, instead of costs, the ratio of input costs and input generated income should be used. As income directly relates to prices, and these in turn relate not only to the cost price generated by

inputs but to the market situation as well (which may be different depending on whether the market is dominated by monopolies or competing terminals), rating of the weight as cost/income ratio does not seem to be reasonable. In order to estimate dependence between indicators (functional approach), Pels et al. (2001) evaluated the stochastic frontiers of productivity of 34 European airports. Martin-Cejas (2002) has the same approach in the evaluation of 31 airports in Spain. Oum et al. (2002) in similar way analysed the 50 largest airports worldwide (Europe and North America, Asia and the Pacific Region). Yoshida & Fujimoto (2004) looked at 30 airports in Japan. One of the serious issues authors have met was availability of data. The research approach requires a set of comprehensive quantitative indicators.

Among the most recent works there could be mentioned two-stage D.E.A. by Cao and Yang (2011) and total productivity decomposition by Cook, Zhu, Bi, and Yang (2010).

3. Methodology

Productivity is often defined as the ratio between the amount of invested resources and benefits received. In such complex systems as airports and their interactions, the evaluation of productivity becomes problematic, noted by many authors in the works described in the previous section. There are a great many interrelated internal and external indicators. Not all of them are measurable. The indicators of invested resources are usually derived and are described as invested labour and capital. The invested resources generate the output which results in derivative indicators, commonly including the number of served aircraft, passenger and cargo throughput. The input and output consist of a complex of partial indicators.

The literature reflects the division of airport productivity by partial factors and by joint factors. Productivity estimates are substantially related to the airport output by one factor, for example, the number of passengers per unit area of the terminal. This evaluation by one indicator is partial. Productivity by partial factors is measured in several dimensions: the global, partial, specific activities and services for passengers.

Quite a number of assessment criteria according to partial factors are mentioned in the literature, but combined assessment factors are rather scarce. Key issues in assessing airport productivity by combined indicators focus on attributing weights to each of the indicators and determining the functional dependence between the parameters describing input and output.

To evaluate productivity researchers also distinguish parametric and nonparametric approaches. The parametric approach may be described as an attempt to determine the functional relationship between the input and output of certain selected indicators, whereas the nonparametric approach does not require the evaluation of parameters, so there is no need to establish the parameters and their estimates, which is difficult because of a lack of statistical data. The most important procedure in a nonparametric approach is D.E.A.

D.E.A. is a methodology to assess threshold values, rather than mean trends. Suppose we have a set of M airports A_1, A_2, …, A_m (Figure 1), each of which is evaluated through a separate input, for example, number of runways, and a separate output, such as the number of aircraft handled. The input and output of every airport are indicated in the coordinate system. For airports A_1, A_7 and A_6 negative residues were received while for airports A_2, A_4 and A_8 positive residues were received. Every airport that has a positive residue is effective
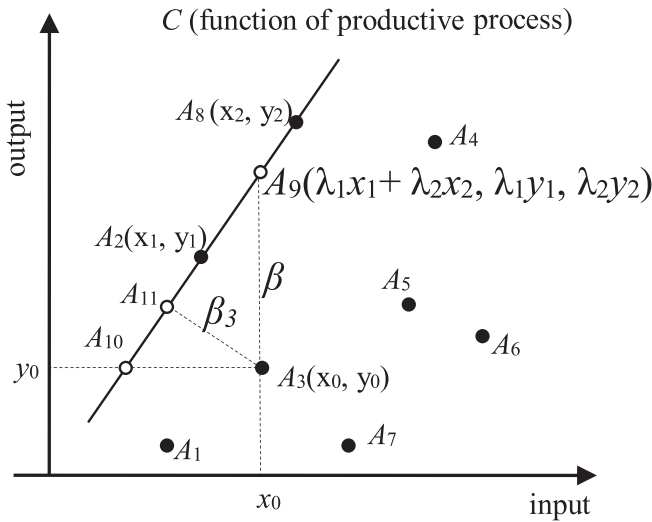
Figure 1. The application of data envelopment analysis. Source: Designed by authors.

at certain inputs. Function C of the effective exploitation process merely points to the productivity at the specific values of the input. The D.E.A. method enables determination of the productivity threshold in assessing its distances for each airport.

The D.E.A. tested each airport to identify which is at a maximum productivity threshold. Letter β marks the scalar coefficient of the specific airport A_3 output Y_2 to achieve maximum productivity level according to the maximum productivity threshold function. Let there be a virtual airport A_9, which can be expressed as a linear function of airports A_2 and A_8 ($\lambda_1 x_1 + \lambda_2 x_2$, $\lambda_1 y_1$, $\lambda_2 y_2$). A_2 and A_8 are the most productive airports, so the growth rate does not apply, or applies but is calculated equal to one. All other unproductive airports will have a coefficient unequal to one. In reality the productivity of such airports is determined not by a single input and output but by lots of them, but in this case, to reflect the productivity in a two-dimensional picture plane becomes impossible.

Further developing the theory of an effective process threshold determination, the vector distance A_3A_{11} can be marked β_k (Figure 1) which by radian geometric equations are calculated for any airport in the set A (A_1, A_8), A, where the scalar expression for each A input and output is available. For each A_k will be a β_k accordingly. β_{kn} vector value of the distance from marginal productivity function C of each airport (A_k) of the investigated range determines the airport unproductivity degree according to n-th index. Provided that two or more airports which are positioned on the marginal productivity line C have the productivity that is maximum in the given range of airports (A_1, A_K), according to the given partial n-th productivity indicator β_{kn} (when the number of partial productive indicators is N), then those two or more airports will show the highest productivity, which is assessed by the 100-point system.

In this case (Figure 1) the estimation of airports A_2 and A_8 will be 100. A 100-point system was basically introduced to unify different scalar values β_{kn} and perform mathematical operations with different scalar values. The airport A_k with the highest β_k for the n-th partial productivity indicator will have the lowest productivity and be assessed as 0. The remaining airports A_k, which are not on the threshold of productivity (not on a

straight line C) and with the β_k for the n-th partial productivity indicator not the lowest, will take various productivity percentages on the straight line C scale drawn between the airports with the maximum productivity and the airport with the lowest productivity. In this way, for each k-th airport we can attribute each n-th partial productivity comparative (relative) index $\beta_{100\ kn}$. The introduction of $\beta_{100\ kn}$ is a significant improvement in D.E.A. because of the possibility to mathematically use productivity values according to different indicators.

The passenger will assess the productivity in one way, the consignor in another way, airport staff in yet a different way, and airport owners or investors will have a different productivity concept. As a solution to this problem researchers use value creation theory. This theory is based on the fact that each parameter, in contrast to the interested party that will assess the productivity, may have a different value.
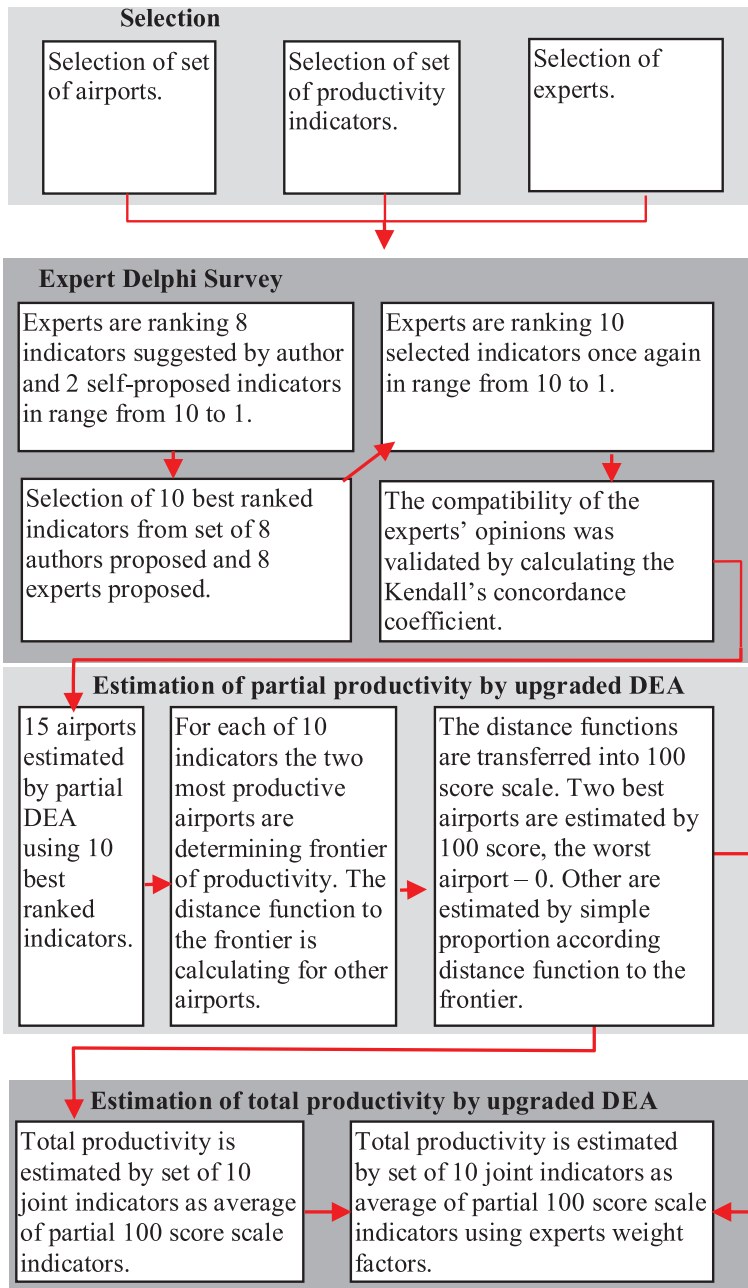
There is an opportunity to compare the productivity of the airport not according to one indicator, but according to a set of indicators. This basically provides an opportunity to determine the total productivity of k-th airport, in a range of K airports, according to N partial productivity indicators. Other authors attempting to use the D.E.A. method of partial exploitation operational indicators to calculate the general comparative productivity did not see the possibility of introducing this relative value, so the calculation and justification of the total (combining a number of indicators) productivity was essentially the main problem of D.E.A. Mathematical operations with productivity indicators which have different dimensions are not possible to perform by means of D.E.A., so the aim is to harmonise the dimensions by expressing some indicators over others. The transition to the relative indicators was largely based on the approaches of value theory.

The determining factor of comparative analysis is not the expression or dimension of productivity, but the ratio of productivity indicators with other similar indicators of airports. With each k-th airport productivity indicator $\beta_{100\ kn}$, by means of a simple arithmetic mean principle we can calculate the total productivity indicator $\beta_{T100\ k}$ for each airport. It is significant that these $\beta_{T100\ k}$ values can be compared with each other only within the range of airports (A_1, A_K), whereas comparison with other airports from other ranges does not make sense. Yet, in determining TCAP $\beta_{T100\ k}$ there are still two major problems. First, which partial productivity indicators β_k must be assessed (i.e., $\beta_{100\ kn}$, where n ranges from 1 to N – range determination); as the range of productivity indicators can be very large, with an increasing quantity of indicators the problem of statistical information presence and accumulation will increase.

The second problem is whether the productivity indicators are equally important in respect to value theory, when the T.C.A.P. is determined on their basis. The answers to these two problems are found in airports value theory. The best balance of interests of all interested parties is reflected by the airport representatives. Expert assessment largely solves the first problem, when the experts select a range of partial productivity indicators, according to which the total productivity rate will be calculated. The second problem is solved by referring to experts by assigning weighted values. Using each of the $\beta_{100\ kn}$ weighted values of each n-th index $\beta_{100\ kn\text{-}leverage}$ and applying $\beta_{100\ kn\text{-}leverage}$ for each k-th airport by the mathematical aggregation principle, an empirical example with this approach applied is given in section 4.

The algorithm of empirical research is presented in Figure 2.

Selection

Selection of set of airports.	Selection of set of productivity indicators.	Selection of experts.

Expert Delphi Survey

Experts are ranking 8 indicators suggested by author and 2 self-proposed indicators in range from 10 to 1.	Experts are ranking 10 selected indicators once again in range from 10 to 1.
Selection of 10 best ranked indicators from set of 8 authors proposed and 8 experts proposed.	The compatibility of the experts' opinions was validated by calculating the Kendall's concordance coefficient.

Estimation of partial productivity by upgraded DEA

15 airports estimated by partial DEA using 10 best ranked indicators.	For each of 10 indicators the two most productive airports are determining frontier of productivity. The distance function to the frontier is calculating for other airports.	The distance functions are transferred into 100 score scale. Two best airports are estimated by 100 score, the worst airport – 0. Other are estimated by simple proportion according distance function to the frontier.

Estimation of total productivity by upgraded DEA

Total productivity is estimated by set of 10 joint indicators as average of partial 100 score scale indicators.	Total productivity is estimated by set of 10 joint indicators as average of partial 100 score scale indicators using experts weight factors.

Figure 2. The algorithm for empirical research. Source: Designed by authors.

4. Results

First, a range of airports $K(A_1, ..., A_k)$ selected for study is determined. To gain practical relevance, the 15 major European Union airports by passenger volume in 2013 were selected (Figure 3).

Figure 3. The location of 15 EU airports. Source: Designed by authors.

The criteria selection problem has been addressed by the available (secondary) data analysis and expert interviews. Based on the work of other researchers, eight partial airport productivity indicators were selected. Expert (selected on the basis of the investigated area) survey was used to extend a list of partial exploitation efficiency indicators and to determine the weights of partial exploitation efficiency indicators. Fifteen experts were selected – the same as the number of airports surveyed. The Delphi method was selected for the survey of experts. In the first round of the survey by the Delphi method, experts were provided with eight partial productivity indicators: PAX/LAND, AIR/LAND, AIR/TAXITIME, PAX/RW, PAX/RWA, FR/RWA, PAX/TAXITIME, AIR/DELTIME. Here: PAX = number of passengers per year, AIR = number of aircraft movements per year, LAND = area of airport territory, RW = number of runways, RWA = max length of the runway, DELTIME = cumulative time of delays per year, TAXITIME = time of taxiing. Eight additional indicators were added to the list by the experts: PAX/TERMAREA, PAX/GATES, AIR/RW, AIR/RWA, AIR/TERMAREA, AIR/GATES, FR/LAND, FR/RW; here GATES = number of gates, FR = volume of freight served, per year. In the second round of expert interviews the same 15 experts were provided with a list of 10 indicators of highest ranks and experts were asked to rank the indicators again. Survey results are presented in Table 1.

The mean rate value (Figure 4) is determined by the formula in both, the first and second rounds:

$$\bar{r}_n = \frac{\sum\limits_{e=1}^{E} r_{en}}{E},$$ (1)

t_{jr} = evaluation of n indicator by e expert, E = number of experts. The compatibility of the experts' opinions was validated by calculating the Kendall's concordance coefficient W and its significance χ^2.

Table 1. The first and second round expert panel results.

Round indicator	Suggested by the author										Suggested by experts in the first round					
	PAX/LAND	AIR/LAND	AIR/TAXI TIME	PAX/RW	PAX/RWA	FR/RWA	PAX/TAXI TIME	AIR/DEL-TIME	PAX/TER-MAREA	PAX/GATES	AIR/RW	AIR/RWA	AIR/TER-MAREA	AIR/GATES	FR/LAND	FR/RW
I	5.67	7.33	4.67	5.87	4.33	2.13	0.20	0.00	2.47	3.47	6.67	5.20	3.80	2.07	0.53	0.60
II	7.00	9.13	4.53	7.33	4.33	n.r.	n.r.	n.r.	2.40	3.40	6.93	5.73	4.40	n.r.	n.r.	n.r.

n.r. – not ranked.
Source: Data from authors research.
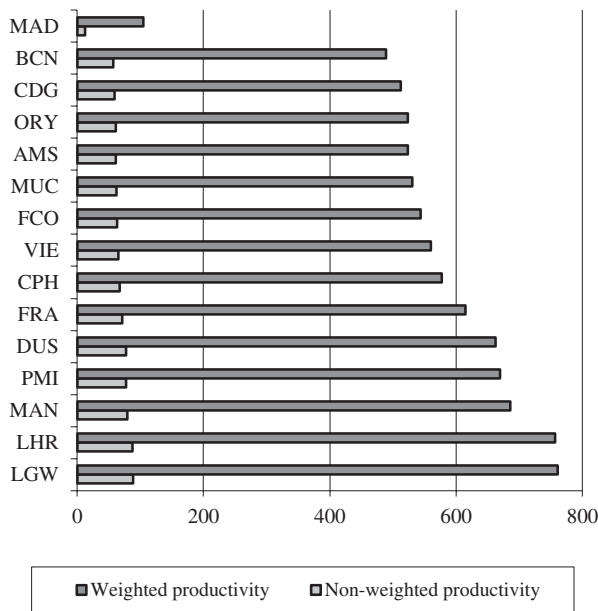
Figure 4. Productivity countdown of 15 European Union airports. Source: Designed by authors.

Then according to each partial productivity indicator through D.E.A. methodology and the authors' method presented in section 3, the two most effective airports are identified with the productivity of 100%, which is measured by a given partial productivity. The remaining airports are ranked from 0 (lowest operational productivity rating) to 100 by vector distance from the threshold productivity line. The data for each of the partial productivity indicator are presented graphically, and the vector distance from the threshold productivity line for each airport is presented in the tables below the graphs. At the same time the tables show recalculated productivity values in the system of 100 points. Figure 5 shows an example of D.E.A. partial productivity. Partial productivity results in the system of 100 points are relative values reflecting the ratio of partial productivity indicators between the airports, and this relationship can be estimated by the sum of the partial productivity values according to Equation (2).

$\beta_{T100\,k}$ for each k-th airport, as calculated by n-th partial index obtained from the equation:

$$\beta_{T100\,k} = \frac{\sum_{n=1}^{N} \beta_{100\,kn}}{N}. \tag{2}$$

Non-weighted indicators of partial productivity of airports are presented in Table 2. Weighted indicators of partial productivity of airports are presented in Table 3. Having evaluated 15 airports under the upgraded D.E.A., the largest comparative productivity by non-weighted indicators was obtained from London Gatwick airport (LGW) – $\beta_{T100\,k\text{-}}$ = 88.43, the lowest, Madrid Barajas airport (MAD) – $\beta_{T100\,k\text{-}}$ = 12.40. The largest comparative productivity by weighted indicators was obtained from London Heathrow airport (LHR) – $\beta_{T100k\text{-}}$ = 760.47, the lowest – Madrid Barajas airport (MAD) – $\beta_{T100k\text{-}}$ = 104.42.
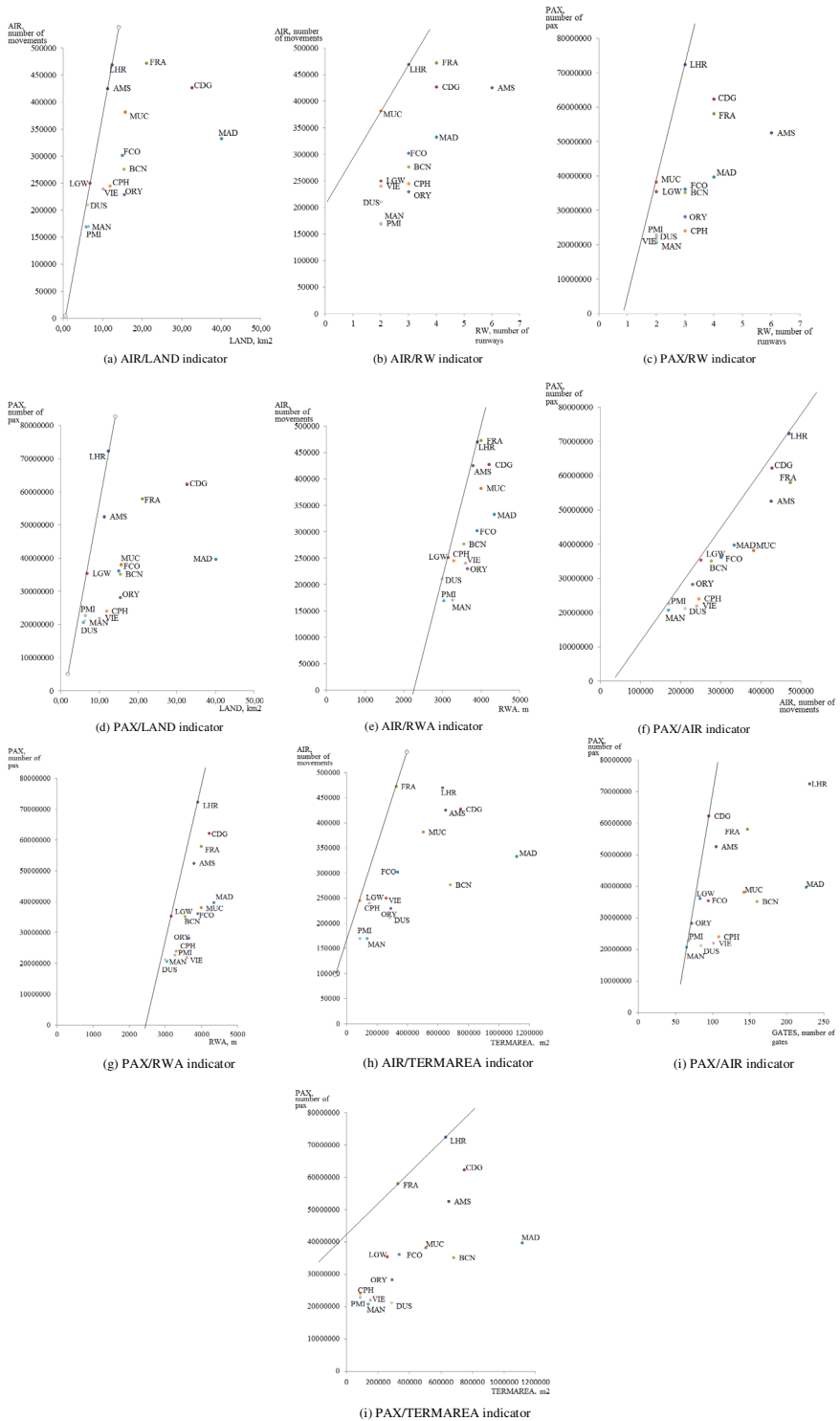
Figure 5. Partial productivity indicators. Source: Designed by authors.

Table 2. Non-weighted indicators of partial productivity.

	AIR/ LAND	AIR/ RW	PAX/ RW	PAX/ LAND	AIR/ RWA	PAX/ AIR	PAX/ RWA	AIR/ TER-MAREA	PAX/ GATES	PAX/ TER-MAREA	β_{T100k}
LHR	100.00	100.00	100.00	100.00	100.00	100.00	100.00	67.22	12.61	100.00	87.98
CDG	31.46	57.64	63.83	33.14	50.14	84.45	53.31	49.68	100.00	71.70	59.53
FRA	72.25	72.47	60.35	66.66	90.58	24.58	65.03	100.00	62.61	100.00	71.45
AMS	99.87	0.00	0.00	94.19	94.44	36.46	73.17	60.02	88.44	62.57	60.92
MAD	0.00	26.96	45.39	0.00	0.00	49.07	0.00	0.00	0.00	0.00	12.14
MUC	82.22	100.00	100.00	74.09	56.33	0.00	28.83	70.72	56.26	49.06	61.75
FCO	77.67	45.36	70.42	75.01	36.96	57.17	34.24	79.81	95.34	59.82	63.18
LGW	100.00	57.16	97.78	100.00	97.77	96.75	100.00	82.25	87.52	65.04	88.43
BCN	74.55	37.07	69.64	73.56	65.03	73.71	64.00	39.97	42.59	28.69	56.88
ORY	70.53	21.80	63.98	70.16	36.75	77.89	42.50	76.49	98.94	49.43	60.85
MAN	96.45	30.75	85.77	96.14	79.21	90.30	83.29	86.19	100.00	48.97	79.71
CPH	83.32	26.79	60.54	79.26	80.18	43.66	66.33	100.00	72.43	59.18	67.17
PMI	94.90	30.96	87.42	95.53	55.42	100.00	66.86	91.54	98.95	56.79	77.84
VIE	88.71	53.79	86.79	83.83	46.14	37.16	35.59	92.62	76.17	50.02	65.08
DUS	98.74	44.22	86.16	95.34	100.00	57.95	88.50	74.92	87.33	37.17	77.03

Source: Data from authors research.

Having the set of the 15 largest European Union airports, two important outcomes of the empirical research were found. The first is that productivity count down did not differ between weighted and non-weighted indicators. So in general this proves the idea of the upgraded D.E.A., when 10 indicators are used for total productivity. The second, and much more important outcome, is related to the location of airports. The productivity of airports located in North Europe is highest in UK airports – LGW and LHR (both in London), and MAN (Manchester). German airports DUS (Dusseldorf) and FRA (Frankfurt) share 5th and 6th position. Near the end of list are French airports CDG and ORY (both in Paris) in 12th and 13th positions, and list finishes with Spanish airports MAD (Madrid) and BCN (Barcelona). To explain the north–south tendency of falling productivity, utilisation cost theory could be used. Heating of terminal buildings during the cold season and clearing the runways impose economy of resources and increasing productivity of capital unit. Otherwise, in the south, terminal heating or runway snow clearing is not used. The matter needs for further investigation in order to prove the proposed hypothesis.

The productivity of airports is defined by a range of indicators, where each of them has a different weight. The expert evaluation of two rounds by applying Delphi method in a 10-point system determined that in the range of explored airports the most significant indicator is the annual number of serviced aircraft per airport area, with a significance index of 8.6. The other most significant indicators selected during the study are as follows: the ratio of the number of aircraft served to the number of runways (significance coefficient is 7.47); the ratio of the number of passengers served during the year to the number of runways (7.00); the ratio of the number of passengers served during the year to airport surface area (6.87); the ratio of the number of serviced aircraft over a year to the longest runway length (5.73).

Table 3. Weighted indicators of partial productivity.

	AIR/ LAND	AIR/ RW	PAX/RW	PAX/LAND	AIR/RWA	PAX/AIR	PAX/RWA	AIR/TERMAREA	PAX/GATES	PAX/TERMAREA	$\beta_{T100k\text{-}weighted}$
LHR	860.00	860.00	860.00	860.00	860.00	860.00	860.00	578.11	108.44	860.00	756.65
CDG	270.52	495.73	548.90	284.98	431.20	726.23	458.49	427.28	860.00	616.62	512.00
FRA	621.37	623.24	519.02	573.24	778.96	211.36	559.24	860.00	538.46	860.00	614.49
AMS	858.88	0.00	0.00	810.03	812.20	313.53	629.28	516.15	760.62	538.14	523.88
MAD	0.00	231.83	390.38	0.00	0.00	421.97	0.00	0.00	0.00	0.00	104.42
MUC	707.13	860.00	860.00	637.15	484.47	0.00	247.97	608.16	483.86	421.88	531.06
FCO	667.94	390.10	605.65	645.07	317.83	491.69	294.49	686.38	819.91	514.46	543.35
LGW	860.00	491.57	840.87	860.00	840.80	832.07	860.00	707.35	752.64	559.36	760.47
BCN	641.13	318.82	598.93	632.60	559.27	633.92	550.42	343.75	366.30	246.75	489.19
ORY	606.58	187.51	550.20	603.36	316.02	669.87	365.47	657.85	850.85	425.06	523.28
MAN	829.50	264.44	737.64	826.77	681.18	776.56	716.25	741.27	860.00	421.10	685.47
CPH	716.53	230.37	520.64	681.66	689.58	375.49	570.47	860.00	622.92	508.97	577.66
PMI	816.15	266.24	751.81	821.55	476.60	860.00	575.03	787.25	850.99	488.37	669.40
VIE	762.88	462.63	746.41	720.96	396.78	319.54	306.11	796.57	655.07	430.20	559.71
DUS	849.18	380.30	740.99	819.95	860.00	498.33	761.08	644.30	751.08	319.70	662.49

Source: Data from authors research.

5. Conclusions

A new model was developed and experimentally tested that can be applied for ranking, combining and comparing productivity indicators of one airport with combined productivity indicators of other airports. The model is based on D.E.A. according to partial indicators. The analysis method was upgraded by the authors through the introduction of weighting parameters to each partial indicator.

The article presents a model which is different from proposed D.E.A. models for measuring airport productivity. The literature review conducted on airport productivity assessment methods showed a problem of identifying a range of indicators as well as fixing data retrieval that may be addressed by appropriate use of value theory and non-parametric evaluation methodology. The assessment of productivity by a non-parametric D.E.A. method according to partial indicators is being developed by researchers, but a scientific problem in comparing the airports by combined indicators remained. The D.E.A. method proposed and upgraded by the authors allows comparison of airports by applying the D.E.A. method according to combined indicators, and this has been proved experimentally. The introduction of the D.E.A. relative index enables escape from dimensions, which being different for different productivity indicators would cause the problem of a productivity aggregation to the total comparative productivity according to combined indicators. The introduction of a relative weight index allows a more accurate assessment of the total productivity by combined indicators.

The proposed model is useful for practitioners, namely airport managers, investors and local governments. The model enables comparison of each airport against competitors in terms of productivity. Estimation of frontier productivity may be used for planning and forecasting of airport turnover.

The empirical research was limited to a selected set of airports. However, it could be used with any set of airports. The set of criteria was defined by group of experts and it could differ within another group of experts. The standardised productivity criteria are not defined in article. This is because of different airport locations and the influence of such factors as climate, land price, and time value. Further research is needed to estimate the relationship of these factors on the set of productivity criteria.

Another limitation is the interpretation of results. The model shows that U.K. and German airports' productivity is the highest, while that of Spanish airports is the lowest. This may be related to a very large range of influencing factors such as climate, business culture, ownership, capacity utilisation, and availability of funds, for instance E.U. aid. Also, it may simply be coincidental. Further investigation related to the influence of factors will follow.

Disclosure statement

No potential conflict of interest was reported by the authors.

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