Determining the sensitivity of Data Envelopment Analysis method used in airport benchmarking

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Abstract: *In the last decade there were some important changes in the airport industry, caused by the liberalization of the air transportation market. Until recently airports were considered infrastructure elements, and they were evaluated only by traffic values or their maximum capacity. Gradual orientation towards commercial led to the need of finding another ways of evaluation, more efficiency oriented. The existing methods for assessing efficiency used for other production units were not suitable to be used in case of airports due to specific features and high complexity of airport operations. In the last years there were some papers that proposed the Data Envelopment Analysis as a method for assessing the operational efficiency in order to conduct the benchmarking. This method offers the possibility of dealing with a large number of variables of different types, which represents the main advantage of this method and also recommends it as a good benchmarking tool for the airports management. This paper goal is to determine the sensitivity of this method in relation with its inputs and outputs. A Data Envelopment Analysis is conducted for 128 airports worldwide, in both input- and output-oriented measures, and the results are analysed against some inputs and outputs variations. Possible weaknesses of using DEA for assessing airports performance are revealed and analysed against this method advantages.*

Key Words: *airport benchmarking, airport efficiency, Data Envelopment Analysis, DEA sensitivity, airport operational performance.*

1. INTRODUCTION

Airport industry has undergone major changes in terms of management. The airports role changed from simple infrastructure elements into profit orientated business. This started in the middle '80 with the privatization of British airports and took many forms like transfer to local authorities, total or partial privatization, sale of shares or external management contract, etc. This transformation of the airports was determined by the need of self-financing, national budgets being unable to fully support all airports operating expenses. Changing an airport orientation towards commercial is not a simple task, because there is little knowledge about administration of an airport as a profit-orientated business. Traditionally, the airport was considered no more than an infrastructure element, like a highway, and was evaluated accordingly, by the maximum capacity and by recorded traffic over a certain amount of time (day, month, year). It is obvious that this way of assessing performance is not proper for a business and other evaluating methods were needed. However, the airport business has some particular aspects that make it different from other business. First of all, the initial capital is huge and the airports assets are expensive, fixed and unconvertible. Second, the airports have no control over the demand of air transportation in their area (unlike the airlines which can operate wherever there is a demand and leave the unprofitable routes). At last, the airports experience high fixed operating costs, that tends to increase financial problems whenever the air traffic drops. Given these particularities we may say that the airport business is special and needs extra care from its managers. Naturally, this commercialization trend led to the need for specific methods for assessing the airports performance. Classical performance indicators for business, like the net profit, were somehow improper for this task, given the fact that not all airports are operating in the same conditions. Some airports benefit from local or central authorities' assistance through direct or indirect subventions, free of charge services such as ATC, security, ambulance or fire fighting, total or partial tax exemption, etc. This assistance is justified by the important role of the airport in the economy of a region, and, in some cases, by the social role. We don't intend to debate the necessity or the fairness of these measures in this paper, we are just pointing out that in the airport business the financial performance can be misleading and therefore other efficiency measures are needed. Another way to determine efficiency is the output/input ratio. This is also difficult to use because an airport is using a wide range of inputs to "produce" a number of different outputs. In order to successfully apply this ratio in the case of airports we need to use the partial performance indicators (a specific output/a certain related input), or to find a way to aggregate these multiple outputs/inputs into single output/input sum. Of course, the simplest way to do this is to use a certain currency to express the value of each input/output, but in the case of airports this is far to be simple. Airports are located in different regions, each one with its fiscal policy, its currency and prices. Therefore, using money as a current denominator for all inputs and outputs is difficult and needs to take into account different other variables that are hard to quantify.

2. USING THE DATA ENVELOPMENT ANALYSIS FOR ASSESSING AIRPORT PERFORMANCE

A method that may be successfully used is the Data Envelopment Analysis. This is based on linear programming and is used to determine efficiency relative to a "best practice frontier" formed by the units with the best results from the whole group. The main advantage of this method is that, due to linear programming, it is able to deal with a large number of variables. DEA was born in 1978, when Charnes, Cooper and Rhodes presented in the paper "Measuring the Efficiency of Decision Making Units" a mathematical model for determining the relative efficiency. The proposed model was focused on inputs and assumed constant returns to scale. Returns to scale represents the way outputs evolve when the inputs are increased. A constant returns to scale means that the outputs are increasing proportional with the inputs increase, while in the case of variable returns to scale, the outputs are increasing in a higher proportion (increasing returns to scale) or in a lower proportion (decreasing returns to scale). The formula developed in 1978 by Charnes, Cooper and Rhodes, further named CCR, may be used to determine the efficiency of the airport 0 (h_0):

$$\max h_0 = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij}} \tag{1}$$

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \le 1 \quad \mathit{for\ each\ j} \tag{2}$$

where v_i and u_r are weights of the x_{ij} inputs, and of the y_{rj} outputs respectively, for the selected airport. Those weights are selected such as the efficiency h_0 to be maximized. The constraints limit the efficiency value to maximum 1. The efficiency frontier is made by all the points with the value 1, and the inefficiency of other units is represented by the segment from the point to this frontier measured on the line from this point to the origin of the reference system. This model is the basic form of DEA, and it has been improved over time. The CCR model assumes a constant return to scale, but this is true only in case of airports that operate at optimal scale. In reality this is hardly possible due to competition, financial constraints, legal framework, etc. Banker, Charnes and Cooper (1984) suggested a change in the DEA model with constant returns to scale (CRS DEA) in order to adjust to the situations with variable returns of scale (VRS), by introducing a condition of convexity for the best practice frontier. The convexity condition ensures that an inefficient company is compared only to companies with similar characteristics. This means that the projection of the point on the best practice frontier is a convex combination of all the observed companies. This is known as the BCC model. For a better understanding of how to determine the relative efficiency with DEA, we will use a simple example, namely that of a comparative analysis between five fictive airports that produce a single output – number of passengers – using two inputs: labour force and capital costs. Table 1 presents the values of these variables. Because of the large differences between the characteristics of these five airports, it is unclear how they should be compared and which of those airports should be chosen as a model for the others. The answer to these questions becomes evident when we plot the points representing the ratio between each input and the output. In our case, the ratios are capital cost per passenger and labour costs per passenger. It is obvious that the lowest ratio of inputs and outputs is the best efficiency; hence, airports that are closest to the origin of the axes are the most effective.

Table 1. Values of the input and output variables for the 5 fictive airports

		Input 1	Input 2	Labour costs/PAX	Capital costs/PAX
	Passengers	Labour costs	Capital		
A	300000	600	600	0,002	0,002
B	200000	400	800	0,002	0,004
C	100000	600	500	0,006	0,005
D	200000	200	600	0,001	0,003
E	100000	300	100	0,003	0,001

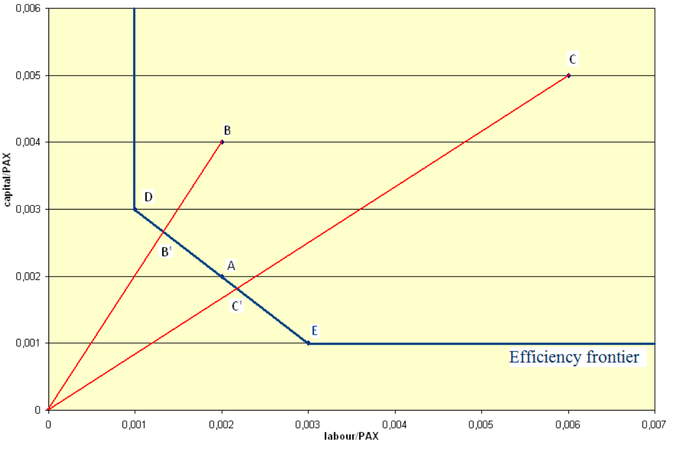

Figure 1: Example of determining efficiency using DEA

The line D-A-E represents the limit of good practice. Airports whose ratio between inputs and outputs are located on this line are considered 100% efficient. So, in our case, airports D, A and E have a coefficient of efficiency of 1.0. Airports beyond the efficiency frontier are considered inefficient, consuming large quantities of inputs to produce one unit of output. To be effective, airports B and C have to reduce ratios of input variables and output in order to reach point B' and C', located on the limit of efficiency. Their current efficiency is given by the ratio of the distance from the origin to point B' and C' respectively, and the distance between point and origin.

$$E_B = \frac{0B'}{0B};\ E_C = \frac{0C'}{0C} \tag{3}$$

In our case, the efficiency score of airport B is 0.667 (66.7%), and that of airport C is 0.364 (36.4%). Analysing the airport B from the figure, we can see that it tends to produce the same results as D and A, which are points on the limit of efficiency. However, in order to establish the relative efficiency, the airport is compared to B', represented through a virtual point located on the frontier. Virtual airport B' is a combination of characteristics of airports D and A. Therefore, in case of using benchmarking to analyse the airport B, it must be compared to airports D and A, representing the most efficient airports with similar characteristics that those of B.

In conclusion, one of the important advantages of the DEA method is that it can identify the corresponding pairs of inefficient airports, with whom those may be compared in order to improve efficiency. The example presented above is easy to understand and to implement, especially graphically (fig. 1), but when we analyse several inputs and outputs, DEA cannot be subject to a simple graphical analysis. It is necessary to use linear programming and a computer to obtain the efficiency coefficients and the optimization potential for each of the airports compared.

This paper goal is to determine the sensitivity of this method in relation with its inputs and outputs. Using the software DEAP 2.1 developed by Tim Coelli, we have applied the BCC to a number of 128 airports from all over the word. We used a number of four input variables, namely the number of employees, number of runways, terminal area and the number of boarding gates.

As outputs, we considered in our calculations number of passengers, cargo traffic expressed in tones and aircraft movements. We used for our calculations only those variables that are expressed in units of measure that can be compared across the whole sample of 128 airports. All financial measures (costs, capital, revenues) were excluded for two reasons. First, we wanted to determine which airports are operating most efficiently, not which ones are able to generate the best income. Second, to be able to use any financial measure, we had to normalize its value according to regional average costs, tax policy and subventions or other protection measures, which is very hard to do, especially for a large sample. However, these measures are present indirectly in our calculation under the form of other inputs (runways, gates, terminals are capital in physical form) and outputs (passenger, cargo and ATM generates revenues and costs).

The model uses a variable returns to scale assumption and was focused on inputs. An output-orientated calculation was also conducted for verifying purpose, the results showing little differences and thereby confirming Coelli and Perelman’s theories. From 128 airports included in the sample, 40 resulted to be efficient when input orientation calculations were conducted. Figure 2 presents graphically the relative efficiency of the 128 airports included in our sample.

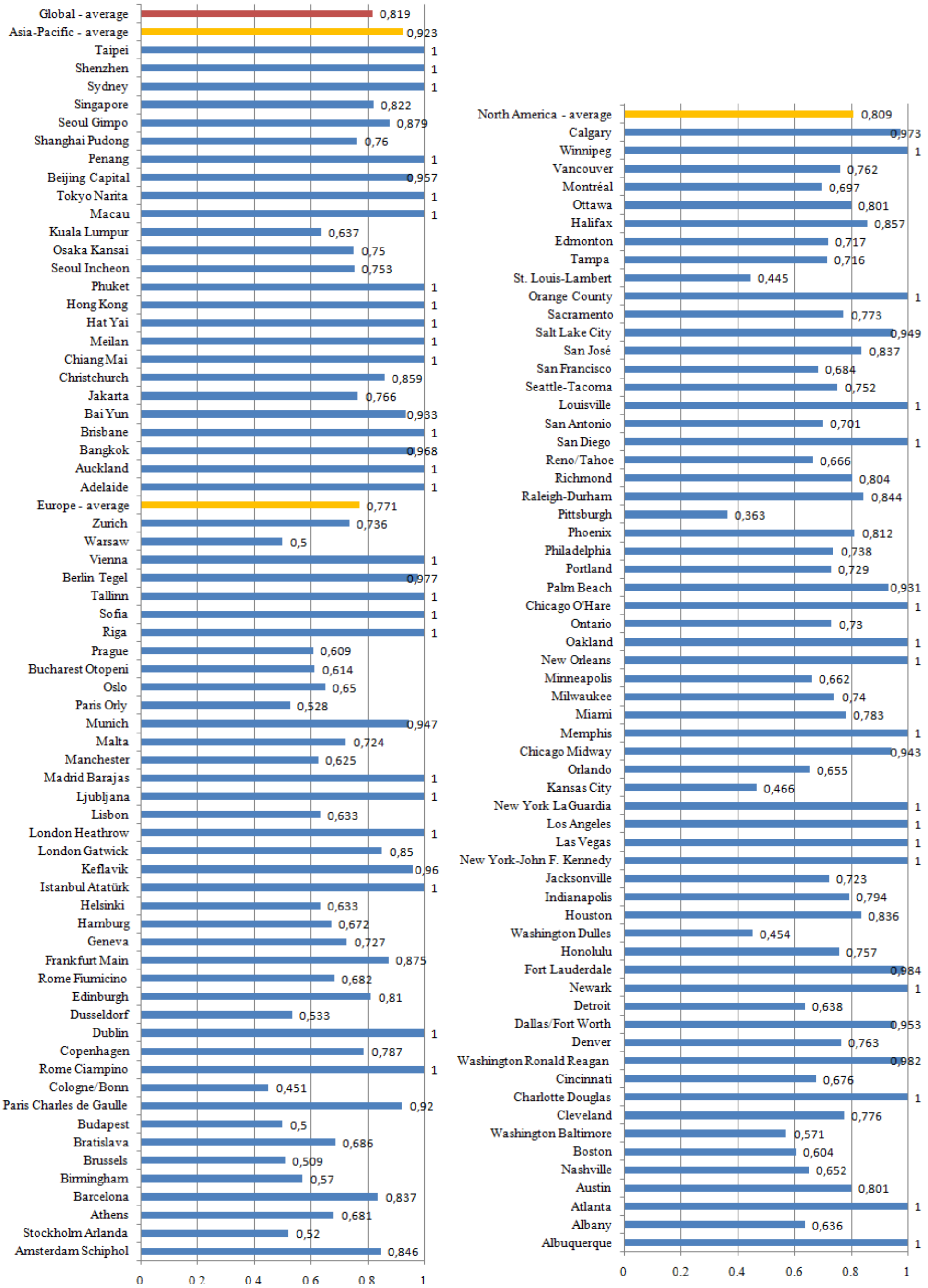

Figure 2: The relative efficiency of the airports (input orientated)

3. DETERMINING DEA SENSITIVITY

DEA is a method that is sensitive to measurement errors. In this paper we wanted to determine how this sensitivity affects the accuracy of the results in different situations. Given the fact that, in case of DEA, efficiency is expressed by reference to the most efficient units from the sample rather than a production function, it is difficult to predict the results evolution in case of changing one or more variables (inputs or outputs). Therefore, we have simulated the most plausible variants and determined the sensitivity of the method for each of these scenarios.

Analysing the results presented in the figure 1, an unexpected result caught our attention, namely the high efficiency of Sofia airport compared to only 61, 4% efficiency obtained by the Otopeni airport. At first glance we can see that Sofia “produces” less form each output (passengers, cargo and air traffic movements) with more employees, bigger passenger terminal area and an approximately similar number of gates. The only input lower than in case of Otopeni airport is the number of runways, Sofia having only one, while Otopeni has two. In case of output -orientated model, the efficiency results are close to our expectations, namely 66,3% efficiency for Otopeni and 49% efficiency for Sofia. This result and the theory which states that input and output- orientated models are generally producing rather close results, we seek an explanation for this anomaly. Analysing the peers of these airports indicated by the DEAP software, it became obvious that Otopeni and Sofia are evaluated by different standards. The only common peer was Rome Ciampino. For Sofia, the other peers were Ljubljana and Penang (Malaysia), both small airports, while Otopeni was reported to Albuquerque and Istanbul, the last airport having 28 million passengers in 2008. In this case Otopeni airport is disadvantaged as compared to Sofia airport, which has rather similar characteristics. Naturally, the questions that rises is whether the input “number of runways” has a disproportionate influence on the results. To find this, we ran the program for a few different situations, to see the influence of each of these situations on the results for the entire sample. Even though the calculations includes all the airports from our sample, we will analyse only the relevant airports (most efficient, most inefficient and the well-known ones).

First, we tested the assumption that Otopeni and Sofia had the same number of runways. For this purpose, we remade the calculations for two fictive situations, the first one with the Otopeni airport having a single runway and all other data remaining unchanged, and the second one with Sofia having two runways and also all other data remaining unchanged. As we expected, the results for the rest of the sample were unchanged because none of the two airports was considered as a peer for other airport and practically no reference was changed for the rest of the airports. In the first situation (Otopeni with one runway), the input-orientated model indicated a maximum efficiency for Otopeni, the same as in the case of Sofia, while the output-orientated model showed an increased efficiency as compared to real data results, Otopeni having a 76,2% efficiency. For the second hypothesis (Sofia has two runways), Otopeni and the rest of the group obtain the same results, while Sofia has considerable lower results: 50% in case of the input-orientated model, and 40,5% in case of the output-orientated model. These efficiency scores reflect better the resemblances and the differences of the two airports, because they are obtained by reference to airports with similar characteristics. To conclude this paragraph, the supposed anomaly (the higher input-orientated efficiency of Sofia airport compared to Otopeni) was not a vulnerability of the program, but the natural consequence of the fact that Otopeni “consumes” double of the input “number of runways” as compared to Sofia.

The analysis of these two fictive situations showed that the initial results were correct, but didn’t answer the question whether or not the input “number of runways” has a disproportionate influence on the results. Therefore we decided to remake the calculations with the initial data, but excluding this input. Before getting to the analysis of the results, we must say that input “number of runways” is an important indicator for both airport capacity and airport capital, and, as such, it must not be excluded from the calculation of the airport efficiency, except for the sensitivity determining purpose.

Using DEAP 2.1 software, we remade the calculations in both input and output-orientated variants. In both cases the results resembled. From 128 airports included in the sample, 29 resulted to be fully efficient, from which 15 were from North America, 7 from Europe and 7 from the Asia-Pacific region. The first fact to be observed is that the number of airports considered to be 100% efficient is lower than in the previous calculation (that included the input “number of runways”).

From 62 airports from North America included in the sample, Albuquerque, Atlanta, Charlotte Douglas, New York JFK, Las Vegas, Los Angeles, New York La Guardia, Memphis, New Orleans, Oakland, Chicago O’Hare, San Diego, Louisville, Orange County and Winnipeg resulted to be efficient in the case of input-orientated model. Newark airport doesn’t obtain fully efficiency and has now an efficiency score of 95,3%. At the bottom of the table situation remains unchanged, the last on our top from this region being Pittsburgh, with an efficiency score of 34,5%, St. Louis, with 42,9%, Kansas City, with 43,3% and Washington Dulles, with 44,1%. The order of the last ranked remains the same as in the case of calculations that included the input “number of runways”, only the efficiency scores recording minor changes, under 3%.

In the output-orientated model there are no changes at the top or at the bottom of the table. Efficiency scores are relatively identical with those resulted from the initial calculations, although this is not a general rule since minor changes appeared in the efficiency scores causing some similar airports to switch places in the table.

In the case of Europe only 7 from 41 airports included in the study were resulted to be fully efficient. These are Rome Ciampino, Dublin, Istanbul, London Heathrow, Ljubljana, Madrid and Vienna. As we expected, Sofia is among the three airports that doesn’t obtain 100% efficiency any more. Other two, Riga and Tallinn, are in the same airport category, with very low traffic, but which obtained a high efficiency score in the initial input orientated calculation because they own a single runway. Now, when we didn’t take into account the input “number of runways”, their efficiency scores dropped considerably, at only 61,9% for Tallinn, 43,3% for Sofia and 37,9% for Riga, which get from the top at bottom of the table. This is explained by the fact that those three airports have high inputs, with the single exception of “number of runways” and very low outputs. In the case of these particular three airports the counter performances are explicable, because, even with a low traffic, airports needs minimal conditions in order to function, reflected in a certain amount of inputs which cannot be reduces further more without affecting the airport functioning. This is not the case of Frankfurt and Munich airports, which experience significant drops in their efficiency scores, Munich from 94,7% to 37,9% and Frankfurt from 87,5% to 56%. The common characteristic of these two airports is the huge number of employees, over 4500 at Munich and near 18000 at Frankfurt. This is the result of the fact that these two airports are providing directly the airport services. The significant impact of the input “number of runways” on the efficiency score is justified by the fact that it is “diluting” the exaggerated value (compared to rest of the sample) of the input “number of employees. Frankfurt’s “projection” on the efficiency frontier will be, in this case, a virtual airport formed by 61,4% Los Angeles, 22% Hong Kong and 16,6% Istanbul, and it will have 2560 employees (compared to 18000 in the present), a terminal area and a number of boarding gates cut by half. As for Munich airport, it’s projection on the efficiency frontier will be a virtual airport formed by 58,7% Charlotte Douglas, 18,2% Madrid Barajas, 16% Rome Ciampino, 6,5% Los Angeles, 0,6% Albuquerque and it will have only 614 employees (compared to 4528 in the present) and a 2,5 times smaller terminal area and number of boarding gates. At the end of table in Europe (input-orientated model, without “number of runways”) we will find Warsaw, with an efficiency score of 28,6%, Koln-Bonn, with 35,6%, Budapest, with 37,4% and Riga and Munich, with 37,9%. Except the last two airports, which we analysed earlier, the others aren’t surprises, because they been fund inefficient in the previous calculations as well. Amsterdam Schiphol had an efficiency score of 84,6% after initial input -orientated calculations. After removing the input “number of runways”, the efficiency score was unchanged. Given the fact that Amsterdam has a number of 6 runways, we expected that the efficiency score should increase, but this didn’t happened indicating that other inputs are also too increased. In the case of Paris Charles de Gaulle airport, excluding the input “number of runways” led to a decrease in the efficiency score, from 92% to 88,6%, indicating that this variable tended to increase efficiency. As in the case of Amsterdam Schiphol, the other inputs are too increased to obtain fully efficiency, especially for the number of employees. This does not happen because these airports are providing airport services, which are traditionally externalized, but because these airports have chosen to excel by high quality service, unlike low-cost airports such as Rome Ciampino, which obtained high operational performance at the cost of sacrificing services quality. In the case of Bucharest Otopeni airport, input-orientated efficiency score remains unchanged, 61,4%,after removing the input “number of runways”, indicating that this input is in line with the other inputs, higher than necessary for the existing traffic.

In the case of output -orientated calculations, the changes in the efficiency scores are not spectacular. There are some changes in the efficiency scores for some airports, but, with one notable exception, these are not significant. This exception is again represented by Munich airport, for which the efficiency score drops from 95,1% to 49,8% once the input “number of runways” removed. Same as in the case of the single runway airports, Munich airport obtain previously a high efficiency score thanks to the relatively low number of runways (two) as compared to the traffic values, despite the fact that the other inputs values are high. From output-orientated calculations without the “number of runways” input, a projection of Munich Airport on the efficiency frontier is a virtual airport formed by 78,8% Atlanta, 20,8% Charlotte Douglas and 0,4% Memphis, and it should have double quantities of all outputs (passengers, cargo and air traffic movements), together with a significantly lower number of employees (560 instead of 4528). As for Frankfurt airport, it fits into the variation tendency for the sample, recording a 3% drop until 87,1%. Projected changes into Frankfurt’s outputs are not high, because it is one of the busiest airports in the world according to traffic values. In order to obtain a maximum efficiency Frankfurt should increase each output by 15-20% and lower the “number of employees” input with 93%. Frankfurt peers are Hong Kong, Atlanta and Chicago O’Hare with weights of 57,9%, 20,3% and 21,8% respectively. Amsterdam Schiphol, Paris Charles de Gaulle and Bucharest Otopeni had no changes in the output- orientated efficiency scores after removing the “number of runways” input. The last ranked in the output orientated efficiency table (without “number of runway” input) are Warsaw, with an efficiency score of 33,6%, Sofia, with 40,3% and Koln-Bonn with 40,6%. The only difference compared to calculations that included all inputs is the 9% efficiency drop recorded by Sofia airport.

In the Asia-Pacific region, the input -orientated calculations, without the input “number of runways”, revealed that seven airports are fully efficient, from a total of 25 airports from this region included in the sample. These were Adelaide, Brisbane, Chiang Mai, Hat Yai, Hong Kong, Phuket and Sidney. Other seven airports don’t obtain maximum efficiency after removing the input “number of runways”, namely Auckland, Meilan, Macao, Tokyo Narita, Penang, Shenzhen Baoan and Taoyuan International (Taipei). Their efficiency scores are, 84,4%, 38,1%, 64,4%, 93,6%, 74,5%, 70,8% and 88,9%, respectively. Five out of these seven airports have a single runway, while the other two, Tokyo Narita and Taipei, have two runways each. It is obvious that removing the “number of runways” input from calculations causes a decrease in efficiency score, especially for those airports having a single runway. Except for the Meilan airport, which has an important drop (over 60%), in the other cases the influence of this input is not that significant as in the case of the three European airports, Riga, Tallinn and Sofia. This may be explained by the fact that the airports in cause have the other inputs much more balanced and correlated with the outputs. The most inefficient airports from Asia-Pacific, according to the input orientated model that excludes the “number of runways” variable, are Meilan, with an efficiency score of 38,1%, Kuala Lumpur, with 40,5% and Jakarta, with 53,1%. Like in the previous calculations, the last ranked airports of the Asia-Pacific region obtain efficiency scores higher than the last ranked from the other regions, only two airports from this region being present among last 15 from the general top, and none of them being ranked in the last five.

As for the output-orientated calculations, exclusion of the “number of runways” input led to a decrease in the number of fully efficient airports, from 12 to 7. These are Adelaide, Brisbane, Chiang Mai, Hat Yai, Hong Kong, Phuket and Sydney. Airports that don’t obtain maximum efficiency after removing the “number of runways” input are Tokyo Narita, with an efficiency of 94,5%, Taipei, with 88,6%, Auckland, with 84,8%, Penang, with 56,8% and Shenzhen Baoan with 72,9%. As we can see, the decrease of efficiency is not radical, indicating that the variable “number of runways” is influencing slightly positive the operational performance. The most inefficient airports form the Asia-Pacific region, resulted from the input orientation calculation without the variable “number of runways”, are Meilan, with an efficiency score of 40,5%, Kuala Lumpur, with 46,6% and Macau, with 48,2%.

The first conclusion that rises from the sensitivity analysis of the DEA method in relation to the input “number of runways” is that this variable has, in general, a positive influence on the efficiency scores of the airports from our sample. In fact, an important impact of this input is observed especially on small airports, where the influence over the efficiency score is very high. As we said, these airports are in an impossibility of reducing inputs under a certain limit without affecting the proper functioning of the activity. The “number of runways” variable is influencing positively smaller airports because these airports have, in generally, a single runway, which is equivalent with a minimum “consumption” of this input. At the airports with higher number of runways it doesn’t appear to be a significant influence of this variable on the efficiency score. This is because the airports with a larger number of runways are usually big airports, with high values of the outputs (passengers, cargo, ATM) and of the inputs (employees, terminal area, boarding gates), and, therefore, the influence of a single parameter becomes low. Both at the sample level and at the regional level, the average efficiency decreased when we excluded the “number of runways” input. This variable influence is higher in the case of input-orientated calculations (naturally, because this represents an input) and lower in the case of output - orientated calculations.

After we’ve analysed the evolution of the results in relation to an input variation, we do the same in relation to an output. For this we chose the “number of passengers” variable, because this was for many time the main indicator of the airport activity.

In order to determine the method sensitivity in relation to this variable, we applied a fictive increase of 25% to the output “number of passengers” for all the airports in the sample. As we expected, the efficiency scores remained the same, both in the input orientated and in the output orientated calculations. This was expected because any percentage increase of two numbers doesn't modify their ratio, and in our case the efficiency scores is obtained by reporting an airport to its projection on the efficiency frontier (this point is a virtual airport expressed as a percentage combination of its efficient peers). To verify this conclusion, we remade the calculations in both input orientated and output orientated variants, using a fictive "number of passengers" output increased by 75% and the results were similar.

Given this, we decided to increase the output "number of passengers" by a fixed number, for all airports in the sample. The value chose was 1, 5 million passengers, in order to be high enough to change the values of the efficiency scores, but low enough not to change the best practice frontier. This value is at the credibility limit for some airports, because such an increase may pass the physical capacity of some airports regarding its facilities. We expected that this fixed change in "passengers number" output to change significantly the smaller airport efficiency scores, but to affect insignificantly the bigger airports, depending on how much means the 1,5 million passenger increase in the total value of this output. This assumption proved to be correct only about the tendency of increasing efficiency for smaller airports, but the values of this variation were far from spectacular, and this only in the output-orientated calculations. The input orientated -calculations showed no variation of the efficiency score for any airport in the sample. This tendency was somehow predictable, because the increasing value for the output was not large enough to change the efficiency frontier, and all the inputs remained the same. Output- orientated calculations revealed a slightly increase average efficiency for the sample, from 78,64% to 79,37%. The biggest influence on the efficiency score was at the Keflavik airport, which recorded a 13,3% increase in efficiency and was followed by Malta airport, with a 9,7% increase. These were the only airports with increases over 5%. From all 128 airports included in our sample, 58 airports had efficiency increase and the rest remained constant. The increase inefficiency was, indeed, related to the airport size:

- All 12 airports that experienced an increase in efficiency score over 2% had less than 10 million passengers per year;
- 13 airports that experienced in increase in efficiency score between 1 % and 1,6% had between 10 and 30 million passengers per year;
- 17 airports experienced an increase of the efficiency score between 0,4% and 0,9%, the largest of them having under 40 million passengers per year;
- 10 airports experienced an increase of the efficiency score between 0,2% and 0,3%, the largest of them having under 50 million passengers per year;
- 6 airports experienced an increase of the efficiency score under 0,1%, all having under 61 million passengers per year.

Even though there were an increase tendency for the efficiency scores, at the top of the table there were no changes and no other airports didn't advanced to the maximum efficiency category. At the bottom of the table there were some slightly changes, but the last three ranked at the sample level remained the same, namely Pittsburgh, Warsaw and Koln-Bonn, their efficiency scores not being influenced by the "passengers number" output increase by 1,5 million.

In Europe, Amsterdam Schiphol recorded a 0,3% increase in technical efficiency, Paris Charles de Gaulle increased its efficiency score by 0,1% and Frankfurt was not influenced by the change of the passenger number with 1,5 million. In Central and Eastern Europe

Budapest and Bucharest Otopeni had efficiency scores increased by 1,4%, Prague by 0,7%, while Sofia, Riga and Tallinn didn't experienced any changes.

The explanation for such a small variations in efficiency scores is the fact that DEA determines the relative efficiency by reporting the airport to its projection on the efficiency frontier formed by weights of its peers. So, even if the variation of this parameter was made by a constant value, inside of group of airports with similar characteristics, this change is equivalent with a relatively similar percentage increase, and this is why the variations are very small.

In order to observe substantial modifications, we need to change a variable enough to change the efficiency frontier or we have to change its value for a particular airport only. In order to change the efficiency frontier we have to make a dramatic modification of an output, values which will be impossible to obtain with the existing inputs. For example, by using a modification, we can obtain a number of air traffic movements greater than the theoretical capacity of the runways, or a number of passengers too big for the area of the terminal. For these reasons we chose to modify, at first one of the time, and then together, one input and one output for Bucharest Otopeni airport, all other data remaining unchanged.

At first we assumed a passengers number increase with the same value, of 1,5 millions, which for Otopeni represents an increase of 19,6%. Even though this may seem a big increase for this airport, this value is credible, especially in the context of moving this year all the traffic from Baneasa airport (which was 1,88 million in 2010, according to Ministry of Transportation). Both in input and output-orientated models, this change led to an increase in efficiency score, from 61,4% to 66,6% in input- orientated calculations, and from 66,3% to 70,5% in the output -orientated calculations. The efficiency scores for the other airports in the sample remained the same, because Otopeni airport didn't have 100% efficiency and, therefore, didn't influence the efficiency frontier.

The next modification targeted an input, namely the number of employees. This variable usually represents the target of all efficiency measurements performed by the managers, because is the only input that can be adjusted according to outputs and with relatively low costs. Otopeni airport had in 2008 a number of 764 employees.

This number is pretty high given the fact that the airport services are mainly externalized. We choose to remake the calculations with a number of 264 employees. This 65% decrease of the number of employees was not entirely arbitrary, being influenced by the passengers-employee parity at some efficient airports from Europe (Madrid Barajas, Rome Ciampino, Istanbul Ataturk, Dublin). The results showed an efficiency increase from 61,4% to 76,1% in the case of input -orientated calculations, and from 66,3%to 68,3% in the case of output -orientated model.

As in the case of changing the number of passengers, the value chose for changing the number of employees didn't determine a change in the efficiency frontier, and, therefore, all other efficiency scores for the rest of the sample remained unchanged.

The next sensitivity analysis consisted of combined modification of the input "number of employees" and the output "number of passengers", values chose being the ones from above. The calculations revealed an efficiency of 78,5% in the use of inputs, increased by 17,1%, and an efficiency of 72,6% in producing outputs, increased by 6,3%. Neither in this case the increase was as spectacular as in the case of changing the number of runways.

This is because DEA is a method of determining efficiency related to the best practice frontier, constructed by the highly efficient units in the group.

Therefore, the variation of a parameter doesn't bring a proportional variation in efficiency score, like in the case of using a mathematical function for expressing the productivity. In the case of variation of the input “number of runways”, for the Otopeni airport it changed the group of similar airports (peers), and therefore it was benefiting from a more favourable comparison. This didn’t happen in the case of passengers and employee variation.

In the last part of the sensitivity analysis we used DEA to determine the efficiency scores of the same airports, grouped in three samples, one for each region. We must say from the beginning of this section that comparing results from different samples is irrelevant, but we did this only to study the effects on the efficiency of these airports from two points of view: a smaller comparison base and a sample containing only airports from the same region (given the fact that airport’s operators tend to imitate each other’s commercial and operational behaviour).

The sample for North America counted 61 airports. The input -orientated calculations showed an average efficiency of 83,9% for these airports, and a number of 19 airports were fully efficient. The results are better than in the case of global comparison, when airports from this region had an average efficiency of 80,9% and only 16 airports were considered efficient.

The same tendency can be observed when we determined the output-orientated efficiency, when 19 airports had maximum efficiency and the average efficiency score was of 81,8%, better than in the case of global comparison when North American airports obtained an average efficiency of 79%, only 6 of them being fully efficient.

From the 41 European airports, 25 obtained 100% efficiency at the input -orientated calculations with regional sample.

The average efficiency was in this case of 91,2%. Amsterdam, Paris Charles de Gaulle obtain maximum efficiency in this sample, even though in the global comparison they didn’t achieve the best results.

We must remind that in the global comparison the European airports had the poorest results from all three regions, with only 10 airports fully efficient and an average efficiency of 77,1%. This situation repeats in the case of output orientated calculations for the regional sample, where 23 airports resulted to be efficient and the average efficiency was of 87,9%, while in case of the global comparison the results were worse (7 airports fully efficient and an average efficiency of 71,7%).

Taking into account that DEA determines efficiency by reporting to the best practice of the group and adding the poor results obtained by the European airports in the global comparison, we may conclude that a part of them suffered by the same degree of inefficiency.

This theory is argued by the efficiency scores obtained by some European airports that now resulted to be fully efficient, but that in the global sample calculations had similar efficiency scores, around 80-90%. The same situation is met at the medium-small airports, where Birmingham, Lisbon, Oslo, Otopeni and Zurich obtain now maximum efficiency, while in the extended sample of 128 airports their efficiency score were around 60-70%.

In the Asia-Pacific region, from a total of 25 airports, after the input-orientated calculations, a number of 20 airports resulted to be efficient and the average efficiency score was of 96,5%.

As with the other two regions Asia-Pacific had better results once the sample reduced to the region level (14 efficient airports and an average efficiency score of 92,3% were the previous results). In the case of output-orientated calculations an average efficiency of 94,7% and 18 efficient airports have resulted; also there were better results as compared to the global comparison where only 12 airport were fully efficient and the average score of efficiency was 89,1%.

The DEA calculations based on regional groups revealed an increase in efficiency scores for the airports from three regions compared to the results obtained by the same airports compared in a global sample. This is a direct consequence of reducing number of airports that are compared against each other and reveals the fact that this method is sample size sensitive.

4. CONCLUSIONS

The sensitivity analysis conducted showed that there are some limitations of the DEA method. These are related to the sample size and the number of variable used. The accuracy of this method is higher if the number of analysed units is higher. The same tendency is present when we take into account the number of variable used.

If the sample size is too low, or the number of inputs and outputs is low, the efficiency scores of the analysed airports tends to increase until the point where little differences in efficiency are showed.

In our particular case it seems that the "number of runways" input has a positive influence over the efficiency scores of the small airports.

This particular aspect may be a subject for further studies, because in the cases of some airports with very low outputs there is always the risk that one input variation significantly change the efficiency scores. To avoid this, we must take into account more variables in order to enhance precision.

Another conclusion that can be drawn is that a parameter variation for one airport affects only the respectively airport as long as the variation is not big enough to change the efficiency frontier.

The variation of parameter with a fixed percentage value for all the airports in the sample doesn't change the results, because the efficiency is calculated by reporting an airport to its projection on the efficiency frontier (this point is a virtual airport expressed as a percentage combination of its efficient peers) and any percentage increase of two numbers doesn't modify their ratio.

Changing a parameter value with a fixed number for all airports from the sample has as a result only minor modifications of the efficiency scores.

This is because DEA determines the relative efficiency by reporting the airport to its projection on the efficiency frontier formed by weights of its peers.

So, even if the variation of this parameter was made by a constant value, inside of group of airports with similar characteristics, this change is equivalent with a relatively similar percentage increase, and this is why the variations are very small.

Even though the results of this method may be found a little too categorical to please the managers, its features and the fact that it can deal with a large number of different inputs and outputs makes DEA a powerful tool for assessing efficiency.

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