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Does Operational Efficiency Depend on the Airport's Size?

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Abstract: This paper presents operational performance analysis using DEA which is short for data envelopment analysis. The study focuses on 9 South African commercial airports. These were divided into different hub groups according to their size. Few airports utilize any type of operational performance indicators for performance evaluation. Operational information such as aircrafts' landing and take-off movements are some of the important data that can be used. Airport performance measures are necessary for stakeholders such as passengers and day-to-day business operations. The study was limited to only two inputs and two outputs. Outputs being passenger throughput and total air traffic movements. The inputs being hourly runway capacity and public parking bays. After DEA was used to evaluate the efficiency of the airports, statistical analysis was done to identify those airports that dominate others in terms of efficiency.

Keywords: DEA, Airports, Operational performance

1. Introduction

Economic Efficiency is a condition whereby there is optimal allocation of every resource in such a way that each person is served in the best possible way and inefficiency and waste are minimized. Technological efficiency in production seeks to identify the optimal combination of factor inputs to produce a given level of output (Investopedia, 2018). A study by Air Transportation Association (ATA) showed that for the year 2017 consumers should benefit from more routes, lower travel costs and are expected to spend 1% of world GDP on air transportation. Governments have earned over $124bn in tax in 2017 and created over 69 million supply chain jobs because of air transportation. Air transportation infrastructure's use costs are high. Inefficiencies in Europe added about €2.9bn to airline costs in 2017. More than 98% of the country commercial traffic is handled by South Africa's airports (Mail&Guardian,2015). According to Airports Company South Africa (ACSA) the airport assets supporting cargo are largely aging facilities, with the exception of King Shaka International airport, where the facilities are still new. According to Tsuen et al. (2013) airport industry in New Zealand has experienced substantial growth over recent years, but only a few studies have analyzed the operational efficiency of that country's airports. They used slacks-based measure (SBM) model and the Malmquist productivity index (MPI). In a 2016 study Cult and McCarthy used stochastic frontier analysis to analyze the efficiency differences for alternative airport ownership types. They found that while form of ownership may matter for cost efficiency, in general its effect is relatively small. Pavlyuk (2016) analyzed the role of spatial heterogeneity in estimation of airports' efficiency. He utilized modern methods of spatial econometrics to identify the importance of spatial heterogeneity for estimates of airports' resource elasticity and efficiency values. A set of utilized models includes the spatial error model, spatial stochastic frontier model. Barros et al. (2013) analyzed technical efficiency in French airports with the inverse B-convex model. Zou et al. (2015) investigated the effect on airport productive efficiency of two major funding sources used by United States airports. A two-stage Data Envelopment Analysis (DEA) modeling approach is employed for the study. Pyrialakou et al. (2012) had seen only a few studies on the connection between airport efficiency and low-cost carriers. In their study, they investigated this connection using data envelopment analysis (DEA). According to Tsuen et al. (2014) few studies have analyzed Asia Pacific airports' operational efficiency. So, to assess airport efficiency they evaluated the operational efficiency of 21 Asia Pacific airports using a two-stage Data Envelopment Analysis (DEA) method. As the benchmarking tool, the multi-dimensional scaling cluster analysis by R-square method was used. 10 operational efficiency factors for the clustering and efficiency estimation of airports in the Asia Pacific region were used in a regression model. In airport studies, Bazargan and Vasigh (2003) applied DEA method to analyze 45 US commercial airports. Initially, a DEA was deployed to analyze the performance measures of airports. Pestana et al. (2007) addressed empirically financial and operational performance of Italian airports using DEA methodology to measure the proximity of the airports to the frontiers of best practices. Curi et al. (2010) analyzed the impacts of Italian government actions on the efficiency of 36 airports. The analysis used the consolidated two-stage data envelopment analysis with bootstrapping. Monikaa et al. (2015) dealt with the problem of qualitative indicators measurement in human resource controlling system with DEA which provided efficiency ratings that made the maximum possible use of the available data. Gitto and Mancuso (2012) used data envelopment analysis to evaluate the impact of regulatory reforms on the technical efficiency of 28 Italian airports. Gillen and Lall (1997) applied Data Envelopment Analysis to assess airports' performance to investigate the performance of airports, and how changes in the industry may have affected them.

Chang et al. (2013) assessed whether geographical characteristics and service strategies have any influence in the performance of Chinese airports using DEA. Coto-Mill et al. (2016) studied the effect of the proportion of cargo traffic relative to total traffic also known as "effect procargo" on technical and scale efficiency at airports using Data Envelopment Analysis (DEA) methodology, a comparative technical efficiency analysis was developed. Suárez-Alemán and Jiménez (2016) used a regression model to investigate passengers' assessments of airports, these may also include implicit evaluation of features that are not directly observable regarding an airport's management and characteristics. Shao and Sun (2016) divided the production process based on air route operational characteristics into two stages i.e. allocation and transport and then two network data envelopment analysis (DEA) models are proposed to analyze the efficiency of the system, passenger transport, allocation and freight transport. Ahn and Min (2014) evaluated the comparative efficiencies of international airports using DEA intended for dynamic benchmarking and Malmquist productivity index which was built on a time-series analysis. In and Hong (2006) used DEA to assess the operational performance of 20 major airports around the world. Barros et al. (2016) analyzed efficiency levels in Nigerian airports using a fuzzy DEA that captured the impact of unobserved managerial ability based on the methodology presented in Alvarez et al. (2004) – the AAG model. Fancelloa et al. (2013) compared performances of different urban networks, using Data Envelopment Analysis (DEA). Farrel (1957) did a conclusive study of road system performance analysis using DEA.Ha et al. (2013) investigated with the help of DEA, the impact of airline market structure on airport productivity. A standard two-stage approach is employed: In the first stage, efficiency of the airports is measured by both the DEA and stochastic frontier analysis. Data envelopment analysis sought a frontier to envelop all data with data acting in a critical role in the process and in such a way measures the relative efficiency of each decision making unit in comparison with other units. Toloo and Tichy (2014) extended both the multiplier and envelopment forms of DEA models and proposed two alternative approaches for selecting performance measures under variable returns to scale. The multiplier form of selecting model led to the maximum efficiency scores and the maximum discrimination between efficient units was achieved by applying the envelopment form. The assessment of economic and technical efficiency is a useful tool for selecting the most appropriate technology for airport operations. Traditional models require that the units being assessed operate with the same technology. To overcome this limitation, they used a non-concave frontier approach that is based on DEA to calculate the techno-economic efficiency and Technological Gap Ratios. (Chena et al.,). Dan Liu (2015) stated that improving operational efficiency has become an important development strategy for many airport companies. He evaluated the efficiencies of aeronautical service sub-process and commercial service sub-process using Network Data Envelopment Analysis. (Adler et al, 2013) applied DEA assuming that the aeronautical output is exogenous, in order to estimate the relative efficiencies of European regional airports over the last decade.

Currently, most DEA studies have focused on both the financial and operational inputs, no studies have been done on operational inputs only. Also, in South Africa performance is normally measured through the help of long-term annual reports. Most DEA Studies that have been done in South Africa have only targeted the academic and banking sectors. Kent and Gerhard (2015) studied the relative efficiency among South African universities from 1994 t0 1997 using DEA based on a sample of 10 of the 21 public universities. In instances where there is a need to check how an organization is doing in the short-term, it could be very difficult or impossible to get quick results. For this reason, this DEA analysis is adopted.

2. Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming technique for used to measure the relative performance of organizational units where there is a presence of multiple inputs and multiple outputs which makes comparisons to be difficult. The CCR model was initially proposed by Charnes et al. (1978). The constraints mean that the ratio of "virtual output" vs. "virtual input" should be less than 1 for every Decision Making Unit (DMU). The main objective is to obtain the ratio of the weighted output to the weighted input. The efficiency of each DMU is measured and hence N optimizations, one for each DMU is to be evaluated. The input-oriented BCC model was proposed by Banker et al and evaluates the efficiency of DMUs by solving a linear program. In their work, Banker et al. (1994) adds computational convenience and efficiency to the article by Banker and Thrall on returns to scale in DEA by modifying one of their suggestions to avoid the need for examining all alternative optima in order to reach a decision. Cooper et al. had a special issue containing papers selected from a presentation in the DEA sessions of the Decision Sciences Institute meetings in Athens, Greece on 4–7 July, 1999. The papers selected represented those papers that survived referee processes that conformed to the rules and standards of the European Journal of Operational Research as well as the editing and suggestions of the editors of this special issue. The unifying theme of these sessions was ''DEA and Its Uses in Different Countries''.

Banker et al. (2003) surveyed the returns to scale in different DEA models. Both the BCC and CCR models were treated in input-oriented forms while the multiplicative model is treated in the output-oriented form. This distinction is not pertinent for the additive model which maximizes outputs and minimizes inputs simultaneously in the sense of a vector optimization. According to Emrouznejad (2003) since DEA's introduction in 1978, it has become one of the preeminent non-parametric methods for measuring both the efficiency and productivity of DMUs. This special issue has its origin in the 10th International Data Envelopment Analysis Conference in 2012 that took place in Natal, Brazil. The theories and methods from economics can be useful in DEA analysis. Using the economics basics, a structural framework is proposed to highlight critical issues in operations management that deserve attention. Examples from industry have been used to illustrate how the framework may provide answers to questions that have received little attention in the research literature (Banker et al. 1995). Toloo and Nalchigar (2008) proposed a new integrated model for determining most BCC-efficient DMU by solving only one linear program. This model is useful for situations where there is a variable return to scale, so has a wider range of application than other models which find the most CCR-efficient DMU.

3. Methodology

3.1 DEA Formulation

Data envelopment analysis often referred to as frontier analysis, was first put forward by Charnes, Cooper and Rhodes in 1978. It is a performance measurement technique which evaluates the relative efficiency of decision-making units (DMUs) for different organizations. A DMU is a distinct unit within an organization that has flexibility with respect to some of the decisions it makes, but not necessarily complete freedom with respect to these decisions. The following methodology will be employed for this study. Different inputs will be explained.

$$Efficiency = \frac{outputs}{inputs} \tag{1}$$

This is the usual measure of efficiency which is often inadequate since most times when measuring the efficiency of organizational units there often exist multiple inputs and outputs.

$$Relative\ Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of inputs} \tag{2}$$

The above formula is the measurement of relative efficiency where there are multiple inputs and outputs. This focuses on a hypothetical efficient unit.

When usual mathematical notation is introduced:

$$Efficiency\ of\ unit\ j = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots}{v_1 x_{1j} + v_2 x_{2j} + \cdots} \tag{3}$$

Where

u_1=weight of output
y_1j=amount of output 1 to unit j
v_1=weight given to input 1
x_1j=amount of input 1 to unit j

DEA can be presented in several forms. The following will be presented to simplify the formulation explanation. Supposing there are K inputs and M outputs for each airport i (i=1,2…n). x_i and y_i are the vectors of the inputs and outputs respectively. For each airport we would like to obtain a measure of the ratio of all outputs to inputs ((u^(') y_i)/(v^(') x_i)) .u and v are the vectors M*1 and K*1 of outputs and inputs weights respectively. To solve for optimal weights:

$$\max_{u,v} \quad (\frac{u' \, y_i}{v' \, x_i}) \tag{4}$$

$$st \quad \frac{u' \, y_j}{v' \, x_j} \leq 1, \mathrm{j} = 1,2 \ldots \mathrm{n}$$

$$u, v \geq 0$$

The above formulation involves computing the values of u and v so that the efficiency measure of the i^thairport is maximized. Solving a problem in the above format is challenging, therefore the duality in linear programming is useful and an equivalent envelopment form of this problem can be used and hence from the above formula follows the next methodology:

$$Min_{\lambda,\theta} \quad \theta \tag{5}$$

$$st \ -y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$\lambda \geq 0$$

$$\theta \, \epsilon \, [0 \; 1]$$

Where

K inputs , M ouputs , I airports
$x_i = K \times 1$ vector of inputs
$y_i = M \times 1$ vector of outputs
$X = K \times I$ input matrix
$X = K \times I$ input matrix
$Y = M \times I$ output matrix
θ is a scalar and λ is an N*1 constant vector

The value of θ obtained will be the efficiency score for the airport. This method assumes constant returns to scale. The problem takes the – the firm and then seeks to radially contract the input vector xi as much as possible. The inner-boundary is a piece-wise linear isoquant determined by the observed data points. The radial contraction of the input vector xi produces a projected point (X λ Y λ) on the surface of this technology. The projected point is a linear combination of the observed data points. The constraints ensure that this projected point cannot lie outside the feasible set. θ is the technical efficiency score and in the range 0 to 1. A score of 1 means that the DMU is on the frontier.

3.2 Mann-Whitney U Test formula

Mann-Whitney U test is a nonparametric test with no assumptions related to the distribution of scores. Some assumptions made are that the sample drawn from the population is random. Mutual independence within the samples is also assumed.

$$U = n_1 n_2 + \frac{n_2(n_2+1)}{2} - \sum_{i=n_1+1}^{n_2} R_i \tag{6}$$

Where

U=Mann-Whitney U test
n_2=sample size2
n_1=sample size1
R_i=sample size rank

4. Research Scope

In airport systems, two performance measures can be used that is financial and operational measures. This research work seeks to answer the following:

- Which airport hubs are relatively more efficient?
- Are these relatively more efficient airports stable over time?
- Which airports statistically dominate others?

Outputs being passenger throughput and total air traffic movements. The inputs being hourly runway capacity and public parking bays.

The input measures were:

- Hourly runway capacity: which is the maximum (landing or takeoff) throughput on average in an hour which could be safely sustained (for an infinitely long time if we have a large pool of aircraft continuously coming to land or takeoff).
- Public parking bays: parking lots which should include reserved spaces and handicapped spaces.

The output measures were:

- Passenger throughput：passenger output relative to input; the amount of passengers passing through a system from input to output.
- Total air traffic movements: total annual landing or takeoff of an aircraft.

5. Results and Discussions

5.1 Relative Efficiency Scores

Results of the CCR model which assumes constant returns to scale indicate that for all the years under study at least 44% of the airports are 100% efficient.

For the large hubs, OR Tambo and Cape Town have been consistently 100% efficient for the six years under investigation. Port Elizabeth, a medium hub and Kimberley, a small hub are seen as the most efficient airports for each of the two hubs.

Table 1: Relative Efficiency Results, 2011-2016

Airport	**Relative Efficiency**					
	2011	**2012**	**2013**	**2014**	**2015**	**2016**
O.R Tambo	1	1	1	1	1	1
Cape Town	1	1	1	1	1	1
King Shaka	0.801	0.793	0.747	0.72	0.698	0.688
Large Hubs Average	0.934	0.931	0.916	0.907	0.899	0.896
Port Elizabeth	1	1	1	1	1	1
East London	0.899	0.813	0.781	0.807	0.746	0.735
George	0.898	0.956	1	1	1	1
Medium Hubs Average	0.932	0.923	0.927	0.936	0.915	0.912
Bram Fischer	0.717	0.781	0.73	0.666	0.619	0.589
Kimberley	1	1	1	1	1	1
Upington	0.549	0.607	0.655	0.73	0.792	0.392
Small Hubs Average	0.755	0.796	0.795	0.799	0.804	0.660

5.2 Average Relative Efficiency

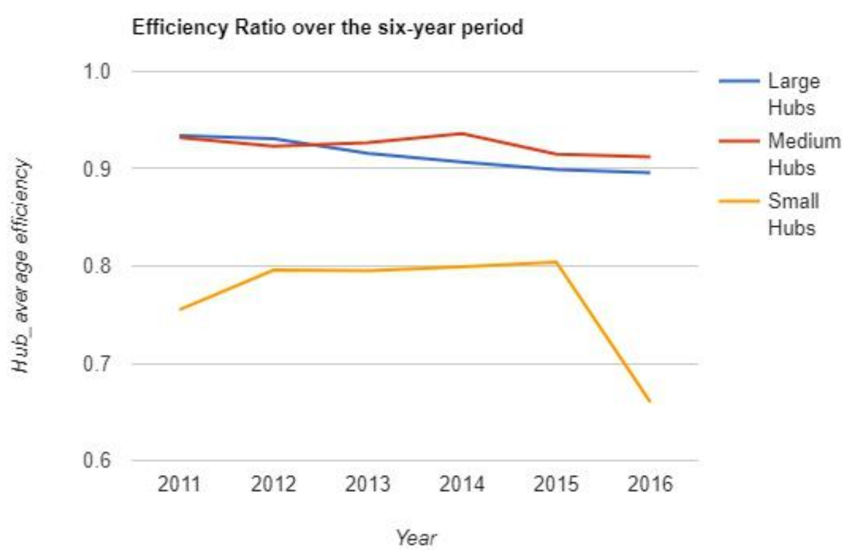

Figure 1: The Average Relative Efficiency scores over the 6-year Study Period

The graph suggests that the relative efficiency is highest and more stable for medium hubs and lowest for small hubs. The airports were grouped according to Large, Medium and Small Hubs. OR Tambo, Cape Town and King Shaka are the large hubs. The medium hubs are Port Elizabeth, East London and George. The small hubs are Bram Fischer, Kimberley and Upington. The average relative efficiency of the airports is highest at 0.936 and for medium hubs.

5.3 Statistical Analysis

5.3.1 Results of the Kruskal-Wallis H Test Results

All the average relative efficiencies are ranked according to value. The 18 values are ranked by the Kruskal-Wallis Test from least to most with the least at 0.660 in the small hubs and the highest at 0.936 in medium hubs. The second highest value was at 0.934 in large hubs. The mean ranks of these average relative efficiencies were computed at 11.3, 13.7 and 3.5 respectively. This respectively ranks medium hubs at the highest mean followed by large and then small airports.

One of the questions the three questions posed by this study was if any hubs were statistically significantly dominated by others. DEA efficiency scores do not fit within a standard normal distribution and hence the non-parametric Kruskal–Wallis test is used for testing. Table 5.2 presents the results for the hubs. At a 5% significance level, the mean ranks of the average relative efficiency scores among the three hubs for 6 years of the study are different. If the P-value ≤ α, the differences between some of the medians are statistically significant. Because the p-value is less than or equal to the significance level of 5%, the null hypothesis which assumes that the groups are from identical populations.is rejected and it is concluded that not all the group medians are equal.

From Table 3, there was a statistically significant difference between the average hub relative scores (H= 11.94, P-value =0.0026).

Table 2: Mean Ranks of the Hubs

Hub Type	N	Mean Rank
Large	6	11.3
Medium	6	13.7
Small	6	3.5

N = the number of years in the study

Table 3: Test Statistics

Chi-Square	11.94
df	2
Asymp. Significance	0.0026

H=Chi-square Value
P-value=Significance Value

5.3.2 Mann-Whitney Test Results

Table 4: Mann - Whitney U Test Results

Pairwise Comparisons	**Mann-Whitney ,U**	**Minimum Value**	**Maximum Value**
Large-Medium	25	7	29
Large-Small	0	7	29
Medium-Small	0	7	29

For pairwise comparisons:

The Mann-Whitney, U-value must be between the minimum and maximum values calculated by the applied software for the average relative score to be statistically insignificant.

A Mann-Whitney test indicated that the average relative scores for large hubs was statistically insignificant compared to medium hubs, U=25, p=0.1492

This same test also indicated that the average relative scores for large hubs was statistically significantly greater compared to small hubs, U=0, p=0.0026. A Mann-Whitney test indicated that the average relative scores for medium hubs was statistically significantly greater compared to small hubs, U=0, p=0.0026.The Mann-Whitney U Test pairwise comparisons are the next logical step if the Kruskal-Wallis H test's null hypothesis is rejected.

5.3.3 Box-and-Whisker Plot

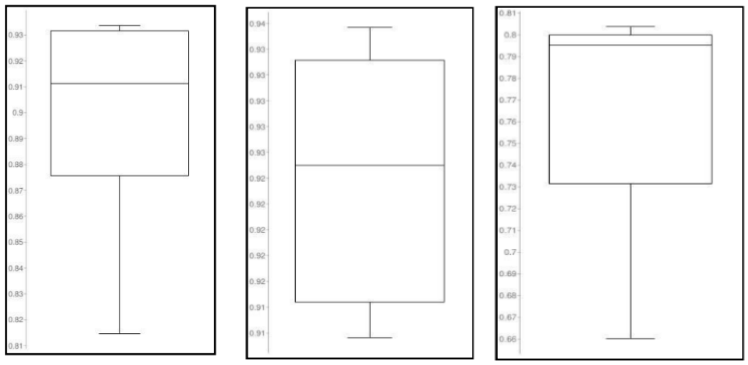

Figure 2: Box-and-Whisker plot for large, medium and small hubs respectively

This plot summarizes a set of data measured on an interval scale. It is used to show the shape of the distribution, its central value and its variability. It indicates whether a distribution is skewed and whether there are any unusual observations in the data set. The plot is useful in visualizing the median values which are used in the Mann-Whitney Test to find either statistical significance or insignificance.

The medians of the hubs were computed at Large=0.9112, Medium=0.9250 and Small=0.7955. According to the calculations above, the medians of the large and medium hubs are +- the same. From this information, it is expected that the difference between large and medium hubs as calculated by Mann-Whitney Test will not be statistically significant. These results support the Mann-Whitney Test results in part 5.3.2.

6. Conclusion

This paper presents a Data Envelopment Analysis of the efficiency of South African commercial airports. The airports are initially grouped into the different hubs according to their size. Relative efficiency scores were generated from an input-oriented minimization DEA model. The evidence shows that the average relative efficiencies of these three hubs i.e. large, medium small are different .There was no year where the average relative efficiency was the same between the three hubs .The results also show that medium hubs tend to be more efficient as compared to large and small hubs . The differences in the relative efficiencies of medium hubs tended to be a little more stable over time that is over the six year period as compared to the large and small hubs. This study presented a Data Envelopment Analysis of commercial hub airports. Average relative efficiency scores were generated through the help of DEA. Kruskal-Wallis statistical Test proved that there exists a significant difference among these types of hubs. Mann Whitney statistical test confirmed that both the medium and large hubs tend to be statistically significantly greater than small hubs. There was no statistically significant difference between large and medium hubs.

This work can benefit both airport managers and practitioners as one of the key factors in the success of an airport in terms of reliability and efficiency is performance measurement .If present performance data of airport is not available ,it will be difficult to discern which areas in the airport's operation need improvement .Through the help of DEA , Key Performance Indicators (KPIs) which are most crucial to the airport's performance can be defined .These KPIs can be used as pointers to show where more work has to be done for better performance. The main limitations of this study were the number of inputs and outputs that were used. There were only two inputs and two outputs. The results would have greatly improved if more inputs (e.g. operating expenses and number of gates) and outputs (e.g. aeronautical and non-aeronautical revenues) had been used.

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