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AN EFFICIENCY ASSESSMENT OF SELECTED GERMAN AIRPORTS USING THE DEA MODEL

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Abstract

The operation of air transport is one of the most significant factors in promoting economic growth and competitiveness within any given region. The present paper deals with an assessment of the performance of Germany's 27 most important airports in terms of their technical efficiency. For this purpose, the authors employed the method of Data Envelopment Analysis. The first part of the paper focuses on a literature review on the use of the DEA method in assessing the performance of airports and air transport. For this DEA a list has been compiled of inputs and outputs that have been used by international authors in their publications to assess airport performance. The second part of the paper describes the methodology of the actual research. The 2016 annual reports from various airports served as the main source of data. The number of employees, number of runways and airport area were selected as inputs. As the outputs, two variables were chosen: number of aircraft movements and the amount of cargo. By applying input-oriented DEA, CCR and BCC models, 13 German airports have been identified that are able to efficiently transform the given inputs into outputs, as they employ the best practices and appropriate processes in their operations management. Five airports can also be described as facilities that have achieved the optimal and most productive size.

Keywords: data envelopment analysis (DEA), airports, technical efficiency, scale efficiency
JEL Classification: C14, C44, C61, L93, R40

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1. INTRODUCTION

The aerospace industry significantly contributes to the economic development of nations and acts as a catalyst for the growth of international trade by providing the fastest available mode of transport. They are also responsible for ensuring safety during passenger and product transport between international airports (Kashiramka et al., 2016). For these reasons, air transport is considered one of the pillars of globalisation. The operation of air transport is a major factor in promoting economic growth and competitiveness, thus improving the quality of life within any given region, while in contrast, poor airport facilities or even their complete absence in a region may hinder economic growth (Żółtaszek & Pisarek, 2017; Gitto & Mancuso, 2010).

In 2016, the world's airports handled 7.2 billion passengers (ACI, 2016). The number of air passengers in the European Union totalled approximately 973 million, with German airports contributing more than one-fifth of that number, i.e. 201 million passengers (Eurostat, 2018). In the "world's top tourist destinations" rankings that are compiled annually by the World Tourism Organisation (2017), Germany ranked 7th in the international tourist arrivals indicator with a figure of 35.6 million in 2016. According to the international tourism receipts indicator, Germany ranked 8th in 2016 with a figure of USD 37.4 billion. According to the ranking of Top airports in the EU in terms of total passengers for 2016, 4 German airports ranked among the top 30, Frankfurt am Main, München, Düsseldorf and Hamburg (Eurostat, 2018).

The air transport business is constantly expanding, with the number of business activities also increasing. Governments are constantly trying to implement policy measures to improve the efficiency and productivity of airport operations (Gitto & Mancuso, 2010). The quantitative expression of efficiency is based on the comparison of inputs spent and outputs achieved. It is therefore necessary to find techniques/methods for assessing performance in air transport in order to help public authorities determine whether some airports can be considered more efficient than others (Danesi & Lupi, 2008).

This paper aims to assess the efficiency of 27 selected airports in Germany in 2016 using the DEA approach. The introduction is followed by an outline of the theoretical background with a focus on the use of the DEA method along with its modifications and combinations with other methods in assessing airport efficiency. The research methodology is then presented, including the specification of the sample of airports to be examined, the data used, and the appropriate models. The conclusion presents the research results.

2. THEORETICAL BACKGROUND

Research into "efficiency" is important in terms of economics and management (Chu et al., 2010), with airport efficiency assessment becoming an increasingly significant area of research. Many scientific papers have dealt with the exploration and measurement of airport performance using parametric and non-parametric methods (Gitto & Mancuso, 2010). The outputs of an appropriately performed airport performance assessment are important for all stakeholders, i.e. airport operators, regulatory authorities, governments, passengers, employees, airlines, local community residents, and industries. In terms of the types of research methodology used to compare and measure airport performance, various techniques are available, such as spatial regression models (Pavlyuk, 2016), the AAG model (Barros et al., 2017), and the Stochastic Frontier Model (Yang & Huang, 2014). Some studies have been conducted using a single method, while others rely on a combination of the above methods. Almost all commonly used approaches to measuring airport productivity and effectiveness are based on the ratio between airport outputs (results) and inputs (resources). In examining the efficiency of airports, it is essential to assess both their financial and operational efficiency and, as the case may be, to evaluate their investment strategy. Data Envelopment Analysis (DEA) is one of the most commonly used non-parametric methods for frontier efficiency analysis. The DEA method is flexible and very easy to use. Thanks to this method, all the above stakeholders can easily compare efficiency between different airports and, in turn, make better decisions (Lai et al., 2015; Chu et al., 2010).

2.1 Data Envelopment Analysis

The DEA method is becoming increasingly popular in studying productivity in various industries. Over the past few years, this method has mainly been used to assess the efficiency of banks, hospitals, universities, and other businesses (Danesi & Lupi, 2008). DEA is a non-parametric method based on linear programming that is used to measure the efficiency and productivity of homogeneous entities called decision units (DMU). This makes it possible to evaluate how efficiently the available resources (inputs) are used to generate a set of outputs relative to other units in the group. DEA makes it possible to calculate in a relatively simple way the relative efficiency of all units assessed within this group. The advantage of DEA is that, while analysing efficiency, it works with multiple factors on both the input side and the output side. Based on the data obtained, an efficiency frontier or production possibility frontier is constructed, which is then used as a reference set to determine the relative efficiency of other production units. DEA allows for a multidimensional approach featuring a one-dimensional evaluation measurement, the efficiency score. Efficiency scores obtained from the DEA model can then be used to assess the efficiency of production units.

Basic DEA models can be generally divided into two groups: input-oriented models and output-oriented models. Input-oriented models estimate the technical efficiency rate, which determines the minimum reduction of input indicators required for the DMU to become technically efficient. In this case, the efficiency score ranges in an interval from 0 to 1, with efficient DMUs achieving a score of 1 and inefficient DMUs a lower score. Output-oriented models estimate the technical efficiency rate, which determines the maximum increase of the output indicators required for the DMU to become technically efficient. Efficient DMUs achieve an efficiency score of 1, while inefficient DMUs achieve a higher score (Zhu, 2014).

In addition, DEA models can be divided in terms of the nature of their returns to scale, namely into models with variable returns to scale (VRS, i.e. the BCC model), and models with constant returns to scale (CRS, i.e. the CCR model). The authors of the historically more recent BCC model, which estimates pure technical efficiency (PTE), are Banker, Charnes, and Cooper (Chu et al., 2010). The CCR model, created by Charnes, Copper, and Rhodes, estimates the overall technical efficiency (OTE), which can be broken down into two distinctly different components: pure technical efficiency and scale efficiency (SE). This allows for a greater insight into the source of inefficiency (Danesi & Lupi, 2008; Kumar & Gulati, 2008).

2.2 Using the DEA method to assess air transport performance

In the professional literature, many studies quite diverse in terms of geographic scope have been published dealing with airport efficiency. Table 1 summarises selected researches. Most of these reports assess the efficiency of airports in one particular country, however, a number of studies compare airports from different countries. The inputs and outputs considered also vary among the studies. On the input side, financial factors (labour and operating costs) along with factors taking into account the physical airport infrastructure (number of runways, terminal floor area, check-in desks, boarding gates) are most often assessed. Indicators concerning passenger numbers, aircraft, and costs are then often used as outputs. Within the various studies, there is no clear determination of the returns to scale; some studies assume variable returns to scale while others build on the assumption of constant returns to scale. The various studies are also divided depending on the orientation of the DEA model selected, with some authors using input-oriented models and others output-oriented models (Lozano & Gutiérrez, 2011).

Below, selected authors who apply the classical concept of the DEA method in their work are summarised. Table 1 lists the inputs and outputs they use along with other data. Martín & Román (2006) use a total of six different approaches to assess the efficiency of Spanish airports using data from 2002, including super-efficiency DEA models and the Surface Measure of Overall Performance method. Malighetti et al. (2007) apply an input-oriented DEA model to assess the efficiency of 27 Italian airports in 2005 and 2006. In their paper, Danesi & Lupi (2008) apply the CCR-I and BCC-I model in assessing the performance of 38 international Italian airports based on data from 2006. Gitto & Mancuso (2010) use two different DEA models to assess the impact of regulatory reforms on the technical effectiveness of 28 Italian airports from 2000–2006. These models make it possible to assess the impact of commercial activities on the overall efficiency of selected airports. In their paper, they divide DEA models into two groups: the physical model and the monetary model. The former analyses the technical efficiency of airport operations, the latter measures the technical efficiency of aeronautical and non-aeronautical activities. A paper by Koçak (2010) uses the DEA model to explore the efficiency of 40 airports in Turkey (2008). It also determines the extent to which inputs should be reduced or outputs increased in order to make airports that the paper identified as inefficient by the research more efficient. Lozano & Gutiérrez (2011) analyse the efficiency of 41 Spanish airports in 2006. An output-oriented DEA model with variable returns to scale is used to calculate technical efficiency. The results of the research conducted show that onehalf of Spanish airports are technically efficient. Lin et al. (2013) measure the efficiency of 62 Canadian and US airports using three different methods: The Index Number Method, the DEA method, and Stochastic Frontier Analysis. By applying the DEA method to selected data, 12 efficient airports were identified. Baltazar et al. (2014) assess and compare trends in the efficiency of selected airports over several years using two tools: DEA and Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). In their paper, they also compare results of the application of the two presented tools in terms of their advantages and disadvantages and seek the best conditions for their application in the decision-making processes of airport management. The research results show that the MACBETH approach is more appropriate compared to methods that are based on the DEA approach. Gok & Ugural (2014) use data envelopment analysis to assess the efficiency of 20 Turkish airports in the 2007–2009 period. The results of their study show that Turkish international airports are more efficient than regional airports. The research conducted led them to the conclusion that between 2007 and 2009, efficiency scores increased for most international airports, while the efficiency of regional airports declined sharply. Pedram & Payan (2015) use the classic DEA model to analyse the efficiency of 7 international airports in Iran in the 2010 to 2013 period. Sopadang & Suwanwong (2016) assess the performance of 19 airports within the Association of South East Asian Nations and 3 other countries in terms of the number of passengers handled with a view to improving the operational performance of these airports. In their paper, they use input-oriented CCR and BCC models and, among other things, they state how the input factors need to be modified in order to achieve better efficiency scores. Pius et al. (2017) use the DEA method to assess the operational performance of airport terminals and examine the effects of modernizing the Murtala Muhammed International Airport in Nigeria based on data from 2006–2014. Wilbert et al. (2017) use input-based DEA models to measure the operational and financial efficiency of 63 public airports managed by the Brazilian Airport Infrastructure Company, working with data from 2010 and 2013.

In assessing the efficiency of airport operations, other authors were not content with the classical approach and went on to modify the DEA method to take into account the specific conditions of the problems being addressed. The selected authors are listed below, and the inputs and outputs used in their publications are included in Table 1. Roghanian & Foroughi (2010) conducted an empirical analysis of 21 active Iranian airports and use DEA and Robust Data Envelopment Analysis (RDEA) to measure their efficiency. In the first step, they use the classical DEA model, which does not take into account the uncertainty associated with input variables. In the second step, the RDEA model is used to study the effect of uncertainty on the ranking of airports. In their empirical study, Chu et al. (2010) analyse 8 airports in Asia and use a two-stage correlative DEA model to determine production efficiency evaluation, considering that airports can be divided into two phases: production and sales. This two-stage model assesses not only the relationship between inputs and outputs, but also the relationship between inputs and intermediate products and the relationship between intermediate products and outputs. Intermediate products are generated out of airport facilities to provide services to airport users. Khezrimotlagh et al. (2012) use a DEA method called the Arash method to explore the efficiency of 17 airports with four inputs and three outputs. Wanke et al. (2016) use the Fuzzy DEA model to capture an uncertainty factor in measuring inputs and outputs obtained at 30 Nigerian airports over the 2003–2013 period. Żółtaszek & Pisarek (2017) use the DEA approach to assess the efficiency of 29 selected national airlines in Europe (for 2013). Two input-oriented models were used to analyse relative technical efficiency: the classical DEA model and the improved Context-Dependent DEA model. The results of the research proved that more than 40% of the airlines under review were classified as efficient. Périco et al. (2017) analyse the efficiency of 16 international Brazilian airports through applying bootstrap data envelopment analysis of selected data from 2010–2012.

At the end of our overview, we recognize a group of authors who combine the DEA method with other scientific methods to assess airport performance. Selected authors are presented below, and the inputs and outputs used can be found in Table 1. Adler & Berechman (2001) applied the DEA method adapted through Principal Component Analysis. Lai et al. (2015) combined the DEA method and the Analytic Hierarchy Process method. Kashiramka et al. (2016) measure the efficiency of selected airports using the BCC model and the Malmquist Productivity Index. Öztürk & Bal (2017) applied the Canonical Correlation Analysis to seek the most effective DEA model.

Tab. 1 – Inputs and outputs used in assessing air transport efficiency. Source: own processing

Source	Unit	*Measurement*	Inputs	Outputs

Adler & Berechman (2001)	26 West-European, Far East and North American airports	*Relative efficiency*	Peak, short and medium haul airport charges Minimum connecting times Number of passengers Number of terminals Number of runways Distance in kilometers to the nearest city centre	5 variables derived from responses to questions posed in a questionnaire
Baltazar et al. (2014)	4 Spanish and 2 Portugal airports	*Efficiency*	Number of runways Aircraft parking stands Passenger terminal area Cargo terminal area Number of boarding gates Number of check-in desks Number of baggage carousels	Aircraft movements Processed passengers Processed cargo
Chu et al. (2010)	8 airports in Asia	*Overall* *technical efficiency* *Pure technical efficiency* *Scale efficiency*	Number of runway Apron number Passenger and cargo terminal area Intermediate products: Taking-off and landing capacity Apron stands Passenger and freight station capacity	Movements Passengers and freight
Gitto & Mancuso (2010)	28 Italian airports	*Technical efficiency*	Number of workers Runway area Airport area Labor cost Capital invested Soft costs	Number of movements Number of passengers Amount of cargo Aeronautical revenues Non-aeronautical revenues
Gok & Ugural (2014)	20 airports in Turkey	*Efficiency*	Terminal size Runway length	Number of passengers Number of aircraft movements Tons of cargo carried
Kashiramka et al. (2016)	46 Indian airports	*Efficiency*	Number of employees Number of runways Square-metre area of building Number of gates Number of cars parking Number of parking bays	Number of aircraft movements Number of passengers Tons of freight Tons of mail
Khezrimotlagh et al. (2012)	17 airports	*Technical efficiency*	Apron Number of baggage belts Check-in counters Boarding gates	Passenger movements Aircraft operations Cargo
Koçak (2011)	40 airports in Turkey	*Technical efficiency*	Operational expenses Number of personnel Annual flight traffic Number of passengers	Number of passengers/area Flight traffic/runway Total cargo traffic Operation revenues

Lai et al. (2015)	24 major international airports	*Efficiency*	Number of employees Number of gates Number of runways Size of terminal area Length of runway Operational expenditure	Number of passengers Amount of freight and mail Aircraft movements Total revenues
Lin et al. (2013)	62 Canadian and U.S. airports	*Operational efficiency*	Number of employees Soft-cost	Number of aircraft movements Number passenger Non-aeronautical Revenue
Lozano & Gutiérrez (2011)	41 Spanish airports	*Technical efficiency*	Total runway area Apron capacity Passenger throughput capacity Number of baggage belts Number of check-in counters Number of boarding gates	Air traffic movements Passenger movements Cargo handled
Lupi & Danesi (2008)	38 Italian international airports	*Technical efficiency Scale efficiency*	Runway length Apron area Number of gates in the passenger terminal	Number of aircraft movements Number of full-service airlines' passenger movements Number of low-cost airlines' passenger movements Tons of cargo loaded and unloaded
Malighetti et al. (2007)	27 Italian airports	*Technical efficiency*	Entire area of the airport Total length of the runways Total number of the aircraft parking positions Terminal surface Number of check-in desks Number of lines for baggage claim	Aircraft movements Passenger movements
Martín & Román (2006)	34 Spanish airports	*Cross* *efficiency* *Super* *efficiency*	Labour Capital Materials	Number of passengers processed Number of tons of cargo transported in the airport Air Traffic movements
Öztürk & Bal (2017)	51 airports in Turkey	*Efficiency*	Terminal pitch size Airport size	Aircraft movements Passenger traffic Freight traffic
Pedram & Payan (2015)	7 international airports in Iran	*Efficiency*	Number of staff working in airports Domestic terminal area in square meters External terminal area in square meters Number of terminals	Number of take-offs and landings of the aircrafts at the airport based on the flight sending and reception at the airport in terms of pas¬sengers Sending and acceptance of loads in every airport in terms of tonnage

Périco et al. (2017)	16 Brazilian international airports	*Operational efficiency*	Number of runways Number of check-in counters Number of aircraft parking bays Passenger terminal area	Passengers processed
Pius et al. (2017)	Murtala Muhammed International Airport	*Operational efficiency*	Number of employees Total cost Total assets	Passenger throughput Aircraft movement Freight or mail Wages
Roghanian & Foroughi (2010)	21 active Iranian airports	*Efficiency*	Number of employees Terminal area Length of runway	Number of movements Number of passengers Amount of cargo
Sopadang & Suwanwong (2016)	19 airports in ASEAN plus 3 countries	*Technical efficiency* *Scale efficiency*	Terminal size Number of runways Lengths of runways Number of gates Check-in desks	Passenger movement
Wanke et al. (2016)	30 Nigerian airports	*Operational efficiency*	Terminal capacity Runway dimension Apron area Number of employees	Total number of movements Number of passengers Cargo throughput Mail throughput
Wilbert et al. (2017)	63 Brazilian public airports	*Financial efficiency* *Operational efficiency*	Total cost	Revenue from unregulated activities Revenue from regulated activities Passenger handling (domestic and international) Air cargo handling and mail (domestic and international)
Żółtaszek & Pisarek (2017)	29 national airlines in Europe	*Technical efficiency*	Fleet Number of employees Number of destinations	Total revenue Number of Passengers Load factor

3. RESEARCH METHODOLOGY

Based on the literature review completed, a classical concept of the DEA method was selected as the most appropriate assessment tool. In this paper, the DEA method is used to evaluate the technical efficiency and scale efficiency indicators of selected German international airports.

3.1 Data collection

The first step was to select the airport sample to be analysed. 27 German airports were selected (see Table 2). The data set is from 2016. In determining the sample, it was decided to focus on international and regional civilian German airports and to exclude military and special airports. In addition, airports for which the necessary quantitative data could not be found were also excluded from the sample.

Tab. 2 – Sample airports in this research. Source: own processing

No.	Airport	IATA code	ICAO code	Classification	Federal state
1	Berlin-Schönefeld	SXF	EDDB	Inter	BB
2	Berlin-Tegel	TXL	EDDT	Inter	BB
3	Bremen	BRE	EDDW	Inter	HB
4	Dortmund	DTM	EDLW	Regio	NW
5	Dresden	DRS	EDDC	Inter	SN
6	Düsseldorf	DUS	EDDL	Inter	NW
7	Erfurt-Weimar	ERF	EDDE	Inter	TH
8	Frankfurt am Main	FRA	EDDF	Inter	HE
9	Frankfurt-Hahn	HHN	EDFH	Regio	RP
10	Friedrichshafen	FDH	EDNY	Regio	BW
11	Hamburg	HAM	EDDH	Inter	HH
12	Hannover-Langenhagen	HAJ	EDDV	Inter	NI
13	Karlsruhe/Baden-Baden	FKB	EDSB	Regio	BW
14	Kassel-Calden	KSF	EDVK	Regio	HE
15	Köln/Bonn	CGN	EDDK	Inter	NW
16	Rostock-Laage	RLG	ETNL	Regio	MV
17	Leipzig/Halle	LEJ	EDDP	Inter	SN
18	Lübeck-Blankensee	LBC	EDHL	Regio	SH
19	Memmingen	FMM	EDJA	Regio	BY
20	München	MUC	EDDM	Inter	BY
21	Münster/Osnabrück	FMO	EDDG	Inter	NW
22	Niederrhein	NRN	EDLV	Regio	NW
23	Nürnberg	NUE	EDDN	Inter	BY
24	Paderborn/Lippstadt	PAD	EDLP	Regio	NW
25	Saarbrücken	SCN	EDDR	Inter	SL
26	Stuttgart	STR	EDDS	Inter	BW
27	Zweibrücken	ZQW	EDRZ	Regio	RP

3.2 Definition of appropriate inputs and outputs for DEA

In the second step, the necessary data were obtained from 27 selected German airports. The main sources of data were annual reports and annual statistics of airport operators and airline alliances. The values for 13 different indicators relevant to the performance assessment of German airports were found in annual reports. Since some data were not available for all airports in the sample, the following variables were excluded in advance from the model: runway area, the number of gates, the number of check-in counters, and the total number of the aircraft parking positions. Conversely, the availability of data led to the pre-selection of inputs and outputs for the DEA model, as clearly shown in Table 3. In this study, 6 input and 3 output characteristics were considered. Table 3 lists the units of measurement and names of the variables used for these inputs and outputs.

Tab. 3 – Units of measurement and labels for inputs and outputs. Source: own processing

	Labels	Variable	Units
Input(s)			
Number of employees	EMPLOY	Total number of people employed in an airport (both part-time and full-time, excluding the number of apprentices, trainees and temporary staff)	unit
Number of terminals	TERM	Number of terminals	unit
Number of runways	RUNW	Number of take-off and land-off runways	unit
Airport area	AIRAREA	Total area of the airport	hectare
Capacity	CAP	The approximate number of passengers that can be handled by the airport per year	million units
Distance from the city center	DISTANCE	Distance from the city centre (for airports serving two cities, the average distance)	kilometres
Output(s)			
Number of passengers	PASS	Total number of passengers who arrive at or depart from the airport	unit
Number of aircraft move-ments	AM	Total number of plans regarding landing and takes-off from the airport	unit
Amount of cargo	CARGO	Total amount of cargo	tons

When selecting inputs and outputs, the following key aspects should be respected: a) the suitability of the selected variables with respect to the economic importance of technical efficiency;

b) the availability of required data for all DMUs; c) the optimum number of inputs and outputs relative to the number of DMUs; d) the uniqueness of the information contained in the input and output points; and (e) the high information value of the continuity between inputs and outputs. With respect to item c), according to Zhu (2014), it is recommended that the minimum number of DMUs is at least three times the aggregate number of inputs and outputs. With regards to item d), information should not be duplicated in both the input group and the output group. According to item e), there should be a strong connection between inputs and outputs, i.e. the outputs included in the DEA model should be generated directly by the relevant inputs. For the purposes of assessing the degree of connection, the correlation coefficient values were calculated for all variables (see Table 4).

Tab. 4 – Correlation between considered variables. Source: researchers' own processing

	EMPLOY	TERM	RUNW	AIRAREA	CAP	DISTANCE	PASS	AM	CARGO
EMPLOY	x								
TERM	0.301	x							
RUNW	0.658	0.488	x						
AIRAREA	0.835	0.357	0.793	x					
CAP	0.983	0.412	0.714	0.838	x				
DISTANCE	-0.042	-0.253	-0.216	0.044	-0.084	x			
PASS	0.952	0.476	0.725	0.808	0.986	-0.093	x		
AM	0.948	0.509	0.726	0.819	0.982	-0.116	0.989	x	
CARGO	0.728	0.190	0.755	0.848	0.721	-0.048	0.706	0.676	x

Based on the results of the correlation analysis, the EMPLOY, RUNW, and AIRAREA variables were used as inputs, and AM and CARGO were used as outputs for efficiency measurement.

3.3 Construction of the DEA models and calculation of the technical efficiency score

In analysing the efficiency of the selected airports, input-oriented DEA models were used, namely BCC-I and CCR-I. The classical BCC-I model assumes variable returns to scale and can be written as an equation (1) meeting the condition of convexity (2).

With the CCR-I model operating under constant returns to scale, the condition of convexity is removed from the previous equation (2).

$$
\begin{aligned}
&E_0 = \min .\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)\\
&\text{s.t.} \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- = \theta X_{i0}, i = 1,\ldots,m,\\
&\sum_{j=1}^{n} \lambda_j Y_{rj} - s_i^+ = Y_{r0}, r = 1,\ldots,s,\\
&\lambda_j, s_i^-, s_i^+ \geq 0, j = 1,\ldots,n, i = 1,\ldots,m, r = 1,\ldots,s.
\end{aligned} \tag{1}
$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2}$$

In the next step, the technical efficiency (TE) score was determined for each airport. All calculations were made using the OSDEA-GUI software. A score of 1 is obtained by an airport that does not show any signs of inefficiency as compared with other related airports. A score of less than 1 indicates an inefficient airport. The score determined using the BCC-I model is called pure technical efficiency (PTE), which indicates how well (i.e. efficiently) inputs are transformed into outputs. The score determined using the CCR-I model is called overall technical efficiency (OTE), which can be broken down into pure technical efficiency and scale efficiency components. In the next step, the scale efficiency (SE) score was therefore calculated according to equation (3). Using the scale efficiency SE, it is subsequently possible to measure the degree to which an airport can improve its efficiency by changing its size.

$$SE = OTE/PTE \qquad (3)$$

The source of the scale inefficiency of individual airports may be either decreasing returns to scale (DRS) or increasing returns to scale (IRS). The type of returns to scale can be determined using the sum of the weights λ of peer units (Zhu, 2014). If $\sum\lambda j = 1$, the airport is classified as scale efficient and operates under constant returns to scale (CRS). If $\sum\lambda j > 1$, the airport operates under DRS conditions and it is recommended that the size of operation or the scale of activities should be reduced in order to eliminate scale inefficiency. On the contrary, if $\sum\lambda j < 1$, the airport operates under IRS conditions and it is recommended that the size of its operations should be increased in order to eliminate scale inefficiency.

4. RESULTS AND DISCUSSION

Firstly, the BCC-I model was applied to data on 27 German airports. This model assumes variable returns to scale and provides the pure technical efficiency score (PTE). The average pure technical efficiency score of the airports is 0.8662. The BCC-I model classified 13 airports (i.e. 48.15%) as efficient, meaning that these facilities are able to efficiently transform the given inputs into outputs. Regardless of their size, they can be expected to use appropriate practices and processes in operations management. According to the PTE score, a ranking was made in which all efficient units were ranked in the first position. The remaining airports, which were classified as inefficient according to the BCC-I model, require an amount of inputs that is much greater than optimal in order to generate the given level of outputs. Their position in the ranking was 14th–27th; the worst-ranked German airports were Erfurt-Weimar and Hannover-Langenhagen. In an input-oriented model, the general recommendations for such inefficient airports include changing the practices and processes currently used in controlled operations so as to reduce the level of inputs to achieve the current level of outputs. A detailed overview is shown in Table 5.

In the second step, the CCR-I model, which provides overall an technical efficiency score (OTE), was applied to the data. Since this model assumes constant returns to scale, it can be used to identify airports that operate at the optimal scale, i.e. the size of their operations is optimal and most productive. The CCR-I classified 5 airports (i.e. 18.5%) as efficient. The average overall technical efficiency score is 0.5828. Detailed results are shown in Table 5. Table 5 also shows that all 5 airports that were classified as efficient according to the CCR-I model are also classified as efficient according to the BCC-I model. This means that the size of these airports' operations is optimal and, at the same time, able to efficiently transform the given inputs into outputs thanks to appropriate management methods, practices, and processes. It is clear that the PTE score is higher than the OTE score, because the CCR-I model takes into account scale inefficiency, which reduces the OTE value. The scale efficiency scores calculated according to equation (3) are shown in Table 5. The average scale efficiency score is 0.6726 and the maximum scale efficiency value is 1 (the maximum value was achieved by 5 airports classified as efficient according to the CCR-I model).

For the group of 8 airports classified as inefficient according to the CCR-I model but are still considered efficient according to the BCC-I model, it is evident that their technical inefficiency is only due to scale inefficiency. It is to be expected that while these airports use the best practices in their operations management, their size is not optimal. The management recommendations for these selected airports should focus on changing the scale of operations (i.e. size) depending on the type of returns to scale.

Tab. 5 – Comparison of the technical efficiency of German airports. Source: researchers' own processing

Airport	CCR-I (OTE)	BCC-I (PTE)	SE	∑λ	RTS	Ranking
Berlin-Schönefeld	0.7992	0.9706	0.8234	0.3996	IRS	18th
Berlin-Tegel	1.0000	1.0000	1.0000	1.0000	CRS	1st
Bremen	0.4269	0.4429	0.9639	0.2202	IRS	25th
Dortmund	0.3562	0.8439	0.4221	0.1185	IRS	19th
Dresden	0.4216	0.8095	0.5208	0.1638	IRS	20th
Düsseldorf	0.9829	0.9986	0.9843	1.3289	DRS	14th
Erfurt-Weimar	0.1434	0.3016	0.4755	0.0474	IRS	27th
Frankfurt am Main	1.0000	1.0000	1.0000	1.0000	CRS	1st
Frankfurt-Hahn	0.3054	1.0000	0.3054	0.1501	IRS	1st
Friedrichshafen	0.3049	0.5536	0.5508	0.0533	IRS	23rd
Hamburg	0.7651	0.7830	0.9771	1.0184	DRS	22nd
Hannover-Langenhagen	0.3201	0.3993	0.8017	0.4081	IRS	26th
Karlsruhe/Baden-Baden	0.5549	1.0000	0.5549	0.1970	IRS	1st
Kassel-Calden	0.5679	1.0000	0.5679	0.1372	IRS	1st
Köln/Bonn	0.9969	1.0000	0.9969	0.7488	IRS	1st
Rostock-Laage	0.5258	0.9759	0.5388	0,0772	IRS	17th
Leipzig/Halle	1.0000	1.0000	1.0000	1.0000	CRS	1st
Lübeck-Blankensee	0.3821	1.0000	0.3821	0.0355	IRS	1st
Memmingen	0.5546	1.0000	0.5546	0.1031	IRS	1st
München	1.0000	1.0000	1.0000	1.0000	CRS	1st

Münster/Osnabrück	0.4685	0.9771	0.4795	0.1860	IRS	16th
Niederrhein	0.3103	0.5499	0.5643	0.0692	IRS	24th
Nürnberg	0.5453	0.7903	0.6900	0.2726	IRS	21th
Paderborn/Lippstadt	0.4261	0.9909	0.4300	0.1806	IRS	15th
Saarbrücken	0.2013	1.0000	0.2013	0.0449	IRS	1st
Stuttgart	1.0000	1.0000	1.0000	1.0000	CRS	1st
Zweibrücken	0.3759	1.0000	0.3759	0.0175	IRS	1st
Mean	0.5828	0.8662	0.6726			
SD	0.2820	0.2135	0.2574			
MIN	0.1434	0.3016	0.2013			
MAX	1.0000	1.0000	1.0000			

The type of returns to scale is derived for all 27 airports based on the sum of the weights λ of peer units (see Table 5). It is clear that only 5 airports (Berlin-Tegel, Frankfurt am Main, Leipzig/Halle, München, and Stuttgart) are operating at the optimal scale – these have been classified as efficient according to the CCR-I model and, therefore, operate under constant returns to scale. Due to their increasing returns to scale, a total of 20 airports can be considered smaller than their optimal scale size. From this perspective, they could resolve their technical inefficiency through expanding their operations, and it can be expected that an increase in inputs will generate a higher than proportional increase in outputs. On the contrary, 2 airports (Düsseldorf and Hamburg) may be identified as bigger than their optimal scale size due to decreasing returns to scale. The management recommendation would be to reduce the scale of these airports' operations since, in their case, inputs generate a lower than proportional increase in outputs.

5. CONCLUSION

The paper presents the results of research on the technical efficiency assessment of 27 German airports. The results of the research may serve as a methodological proposal for assessing airport performance. DEA was selected as the assessment method, namely the input-oriented BCC-I and CCR-I models in which the technical efficiency of the transformation of 3 inputs into 2 outputs was measured. The average OTE score was 0.5828, the average PTE score 0.8662. The average SE score of German airports was determined at 0.6726. In productivity terms, the average German airport is smaller than its optimal scale size because it operates under increasing returns to scale.

By applying two input-oriented DEA models, a ranking was made, with 13 German airports (i.e. 48.15%) identified as being able to efficiently transform the given inputs into outputs, as they use the best practices and appropriate processes in their operations management. Of these airports, 5 (i.e. 18.5% of all airports) could also be classified as airports that achieve the optimal and most productive size since they operate under constant returns to scale. Furthermore, 8 airports were identified as using the best practices in their operations management and are able to perfectly transform inputs into outputs, yet their size is not optimal. From the management perspective, it can be recommended that these airports should change the scale of their operations (i.e. size) depending on the type of returns to scale.

A total of 14 airports were classified as inefficient in both of the aspects under review, i.e. in terms of the efficiency of their ability to transform inputs into outputs (the BCC-I model) as well as in terms of their size (CCR-I). The management recommendations for these inefficient airports should primarily aim at improving the efficiency of the transformation process. These airports should adopt the best practices proven to be successful in the operations of highly efficient airports. At the same time, the optimal size of operations should also be taken into consideration in response to the existing type of returns to scale.

The impacts of applying the selected DEA models could be expanded to include determining the peer units for each of the inefficient airports, which would represent the absolute best practice. Each peer unit is characterised by its weight, which can be used to determine the level of inputs required in order to make a currently inefficient unit reach the efficient frontier.

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