AIRPORTS' OPERATIONAL PERFORMANCE AND EFFICIENCY EVALUATION BASED ON MULTICRITERIA DECISION ANALYSIS (MCDA) AND DATA ENVELOPMENT ANALYSIS (DEA) TOOLS

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ABSTRACT

Airport benchmarking depends on airports' operational performance and efficiency indicators, which are important for business agents, operational managers, regulatory agencies, airlines and passengers. There are several sets of single and complex indicators to evaluate airports' performance and efficiency as well as several techniques to benchmark such infrastructures. The general aim of this work is twofold: to balance the data envelopment analysis (DEA) and multicriteria decision analysis (MCDA) tools and to show that airport benchmarking is also possible using a multicriteria decision analysis tool called Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). Whilst DEA measures the relative performance in the presence of multiple inputs and outputs, MCDA/MACBETH uses performance and efficiency indicators to support benchmark results, being useful for evaluating the real importance and weight of the selected indicators. The work is structured as follows: first, a state-of-the-art review concerning either airport benchmarking and performance indicators or DEA and MCDA tool techniques; second, an overview of the impacts on airports' operational performance and efficiency of emergent operational factors (sudden meteorological/natural phenomena); third, two case studies on a set of worldwide airports and Madeira (FNC) Airport; and fourth, some insights into and challenges for future research that are still under development.

Keywords: Airport Performance and Efficiency, MCDA, DEA, Benchmarking

JEL Classification: L93, O18, R41

1. INTRODUCTION

This work is a part of two MSc theses and one PhD thesis in Aeronautical Engineering – developed under the Business Models for Airport Development and Management (AIRDEV) Project within the MIT-Portugal Program – the aims of which are twofold: to balance the DEA and MCDA tools and to show that airport benchmarking is also possible using a multicriteria decision analysis tool called Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH).

The collected data were related to airports' facilities, considered as inputs – in particular runways, aircraft parking stands, both passenger and cargo terminal areas, check-in desks, baggage carousels and boarding gates – and to airport statistics, namely passengers, aircraft movements and cargo, which were considered as outputs. An emergent operational factor related to sudden meteorological/natural phenomena was also taken into account as input for a self-benchmarking study within Madeira Airport (FNC).

This work is organised as follows: first, a state-of-the-art review concerning airport benchmarking and performance indicators and DEA and MCDA tools and techniques; second, the impacts on airports' operational performance and efficiency of emergent operational factors (sudden meteorological/natural phenomena); third, two case studies concerning a set of worldwide airports and Madeira (FNC) Airport; and fourth, some insights into and challenges for future research that are still under development.

2. AIRPORT BENCHMARKING AND PERFORMANCE INDICATORS

Duarte and Ventura (2013) advocate a systemic approach that helps any organisation to optimise the sequence of activities so that it may improve its results. Benchmarking is a self-improvement tool for any organisation: it allows it to identify its own strengths and weaknesses, to compare itself with others and to learn more about how to improve its efficiency. Benchmarking is an easy way to find and adopt the best practices to achieve the desired results (Spendolini, 1992; Bogan and English, 1994).

Graham (2005) underlines that benchmarking within the airport industry began to be accepted as an important management achievement just fifteen to twenty years ago, mainly because in the past the commercial and business pressures within the airport sector were less pronounced and airports were almost under governmental ownership; nowadays, among several strategies aiming to achieve economic development, the weight that large infrastructures such as airports (and their related performance and efficiency) represent for attracting investment stands out (Prada-Trigo, 2014). Airport benchmarking is a key component of airports' planning procedure (Adler *et al.*, 2013). It is a process that, being statistical, is an accounting one too, used to monitor airports' performance indicators. Benchmarking is a key feature in the implementation of an airport's strategic plan and its importance extends so far as to identify the best practices to increase efficiency and quality (Oum and Yu, 2004). The ACI (2012) summarises the benchmarking process as follows:

- It is about management and organisational change first and measurement and technology second;
- It provides a diagnostic tool to check whether all systems are in alignment and working properly;
- On a self-benchmarking basis, it is an excellent management tool to monitor performance improvements;
- External benchmarking is an effective way to identify best practices to determine whether they can be incorporated into an organisation and to identify faulty practices with the aim of eliminating them;
- A tool to link strategic goals, employee involvement and productivity.

Humphreys (2002) identifies the entities that are particularly relevant to airports' benchmarking process:

- State/government, for economic and environmental regulation reasons;
- Airlines, to compare costs and performance across airports;
- Managers, to run the business;
- Passengers, to evaluate the service that they receive;
- Owners, to understand business performance and how to return the investment.

There are several works on airport benchmarking, each using different performance indicators. Some of them use single indicators, for example the number of aircraft parking positions (ATRS, 2009; Ferreira *et al.*, 2010; ACI, 2012), while others consider complex indicators such as the number of passengers per area of the passenger terminal (Braz, 2011; Braz *et al.*, 2011; Jardim, 2012; Baltazar *et al.*, 2013). The indicators can be divided into two major groups, single and complex, for which we used the DEA and MACBETH tools, respectively. The indicators included in our analysis are shown in Table 1.

Table 1. Single and Complex Indicators

Single indicators	DEA	**Inputs**	Number of Runways
			Number of Aircraft Parking Stands
			Passenger Terminal Area
			Cargo Terminal Area
			Number of Boarding Gates
			Number of Check-In Counters
			Number of Baggage Carousels
			Natural Phenomenon
		Outputs	Aircraft Movements
			Processed Passengers
			Processed Cargo (Ton.)
Complex indicators	MACBETH	**PAX/PAX TA**	Processed Passengers / Passenger Terminal Area
		CARGO/CARGO TA	Processed Cargo (ton.) / Cargo Terminal Area
		MOVS/STANDS	Aircraft Movements / Number of Aircraft Parking Stands
		MOVS/RWS	Aircraft Movements / Number of Runways
		PAX/GATES	Number of Passengers Processed / Number of Boarding Gates
		PAX/CHK-IN	Number of Passengers Processed / Number of Check-In Counters
		MOVS/GATES	Number of Movements / Number of Boarding Gates
		MOVS/BELTS	Number of Movements / Number of Baggage Belts (arrivals)
		OP TIME/TOTAL T	Natural Phenomenon: Operational Time / (24 h 365 days)

Source: Authors

This work tries to demonstrate that it is possible to achieve airport rankings by following a (new) multicriteria approach allowing the proper choice of both the indicators and the related weights. This enables all the interested parties (including passengers) to produce their own ranking, which may be compared at the end of the entire process. Another interesting feature of this method is the ability to compare the performance/efficiency either of the airport with other similar infrastructures or of the airport in different years, thus offering airport managers the possibility to remain in touch with the evolution of the infrastructure.

3. DEA AND MACBETH METHODOLOGIES AND TOOLS

As mentioned, the aims of this study are twofold: to balance the DEA and MCDA tools and to show that airport benchmarking is also possible using a multicriteria decision analysis tool called Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). Whilst DEA is a linear programming-based technique for measuring the relative performance of organisational units in the presence of multiple inputs and outputs (Lai *et al.*, 2012, 2015), MCDA/MACBETH uses performance and efficiency indicators to support benchmark results, being useful for evaluating not only the real importance of the selected indicators but also their correct weight.

3.1 DEA – Data Envelopment Analysis

DEA is a non-parametric method designed to measure, in our case, the performance of an airport using a decision-making unit (DMU). It has several models, and the one chosen for this study was the basic analysis, CCR. The name (CCR) comes from its creators (Charnes, Cooper and Rhodes), and it is also known as CRS (Constant Return to Scale) (Ferreira *et al.*, 2010). The CCR is related to constant returns, and the improvement obtained in the output is proportional to that observed in the inputs. The DEA software used was SIAD (Integrated Decision Support System) (Meza *et al.*, 2005), a CCR model with input-oriented analysis (minimising inputs while keeping output values fixed).

As Meza *et al.* (2005) describe, each k^{th} DMU, $k = 1, ..., n$, is considered to be a production unit that uses r inputs x_{ik}, $i = 1, ...,r$ to produce s outputs y_{jk}, $j = 1, ..., s$. The CCR model described by equation (1) maximises the ratio between the linear combination of outputs and the linear combination of inputs, with the constraint that for each DMU that ratio cannot be greater than one (equation 2). Therefore, for a particular DMU o, h_o is its efficiency, x_{io} and y_{jo} are its inputs and outputs, and v_i and u_j are the calculated weights for the inputs and outputs, respectively. After some mathematical manipulations, the model can be rewritten, yielding a linear programming problem (LPP) (equations 3 and 4).

$$Max \;\; h_k = \frac{\sum_{r=1}^{m} u_r t_r^{j0}}{\sum_{i=1}^{n} v_i w_i^{j0}} \tag{1}$$

subject to:

$$\frac{\sum_{r=1}^{m} u_r t_r^{j}}{\sum_{i=1}^{n} v_i w_i^{j}} \leq 1, \qquad j = 1, 2, \ldots s \tag{2}$$

$$\max \;\; h_o = \sum_{j=1}^{s} u_j y_{jo} \tag{3}$$

subject to,

$$\sum_{i=1}^{r} v_i x_{io} = 1$$
$$\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} \leq 0 \ , \quad k = 1,\ldots,n$$
$$u_j , v_i \geq 0 \quad \forall i, j \qquad (4)$$

As an LPP is solved for each DMU, if we have *n* DMUs, *n* LPPs must be solved, with $r + s$ decision variables. The model just presented is the basis for all other DEA models (Meza *et al.*, 2005).

As Ferreira *et al.* (2010) highlight, DEA tries to maximise the relationship between the goods produced (outputs) and the material spent on their production (inputs) by defining the weight of each output/input. The only constraint of the model is that the efficiency of all DMUs cannot be greater than the unit if using the weight assigned to the analysed DMU. The DEA tool is also useful for defining benchmark units, which are determined by the projection of the inefficient DMUs on the efficient frontier. The way in which this projection is made defines the input/output orientation model: the input-oriented model used to minimise inputs while keeping the values of the output constant or the output-oriented model used to maximise the results without decreasing the assets.

3.2 Multicriteria Decision Analysis Approach and the MACBETH Tool

Since the beginning of history, humans have taken decisions. This is probably one of the most common human tasks. Every day one finds a set of problems and related decisions that are neither easy nor linear to solve. When making a decision, one generally takes into account several criteria that are more or less conflictive. In a stressful situation, if one must consider just one factor, usually the option is the most relevant. Thus, conflicts could exist between several criteria and therefore the decision maker has to consider the pros and cons of each one to reach the final (optimal) solution. This is the basis of a multicriteria decision problem.

As Bana e Costa *et al.* (2012) assert, MACBETH is a user-friendly multicriteria decision analysis approach that requires only qualitative judgements about differences in value to help a decision maker, or a decision advisory group, to quantify the relative attractiveness among several options.

As presented by Bana e Costa *et al.* (2012), MACBETH has a complex formulation, and Gómez *et al.* (2007) describe the basics of this tool's mathematical foundations. Consider X (with $\#X = n \geq 2$) as a finite set of elements (alternatives, choice options, courses of action) for which a group or an individual, J, wants to compare their relative attractiveness (desirability, value).

X defines ordinal value scales, which are quantitative representations of preferences, reflecting numerically the order of attractiveness of the elements of X for J. An ordinal value scale is constructed following a straightforward process; J is able to rank the elements of X by order of attractiveness – either directly or through pairwise comparisons – to determine the elements' relative attractiveness.

When the ranking is defined, it is necessary to assign a real number v(x) to each element x of X, in such a way that:

1. v(x) = v(y) if and only if J judges equal attractiveness between the elements x and y;
2. v(x) v(y) if and only if J judges x to be more attractive than y.

Equally, a value difference scale is defined for X as the preferences' quantitative representation, to be used to reflect not only the order of attractiveness of the elements of X for J, but also the differences in their relative attractiveness, that is, the strength of J's preferences for one element over another. J provides preferential information about two elements of X at a time, firstly by ordinal judgement (of their relative attractiveness) and secondly, if the two elements are not considered to be equally attractive, by expressing a qualitative judgement about the difference in attractiveness between the most attractive of the two elements and the other one.

To ease the judgemental process, six semantic categories of differences in attractiveness are offered to J as possible answers: "very weak", "weak", "moderate", "strong", "very strong" or "extreme" or a succession of these (in the case that hesitation or disagreement arises).

By comparing the elements of X pairwise, a matrix of qualitative judgements is filled in, either with only a few pairs of elements or with all of them (in which case $n \cdot (n - 1) / 2$ comparisons would be made by J).

Thus, before developing any model, it is necessary to obtain as large an amount of data as possible. The next step is to create a decision tree with nodes, that is, a decision model; the nodes correspond to the indicators that will be taken into account, so the choice of nodes is one of the key issues in the development phase.

Subsequently, data need to be obtained to fill the performance table of each indicator; this is a crucial step that even influences the node choice because only if the data collection fills the performance table for each indicator is it possible to use that indicator within the work.

Within the next step, each decider defines the attractiveness of each indicator in the tree; after considering the attractiveness of each node, the decision maker must define the attractiveness difference between each pair of indicators in the model too. Following the introduction of these values for each node, it is possible to produce a robustness table, still giving the opportunity to the decider to adjust the sensibility of the model (Braz *et al.*, 2011).

4. THE IMPACTS OF NATURAL (WEATHER) PHENOMENA ON AIRPORTS' OPERATIONAL PERFORMANCE AND EFFICIENCY

It is well known that aviation presents a high level of sensitivity to the weather, involving major impacts on the safety, efficiency and capacity of aviation operations. Consequently, under those conditions, the capacity of airports is highly reduced by the need to increase the separation between aircraft, the need for additional holdings or the closure of one or even all of the runways, thus affecting their operational performance. Such weather phenomena, from the point of view of airport operations, include thunderstorms, turbulence and gusts, heavy snowfall (Figure 1) and runway icing, low visibility due to fog and, most recently, volcanic ash in the airspace due to volcanic eruptions. As a result, the operational capacity of a region's entire airspace is reduced through delays, diversions and flight cancellations, all of which have severe effects on travellers.

Figure 1. Heavy Rain at Cancun Airport

Source: Morales, 2012

An airport has a number of basic characteristics, all of which are considered to be combined with specific weather hazards, such as local weather phenomena and climatic conditions, the topography of the region, the orientation of the runways and so on. However, due to (sudden) climate changes, these phenomena will each become more common and produce growing negative impacts; therefore, in our opinion, an individual self-benchmarking study has to be performed for each airport – or the most vulnerable ones – to investigate its susceptibility to adverse weather conditions, since the conclusions reached for one airport of course do not automatically hold for others (Sasse and Hauf, 2003).

5. CASE STUDIES

In the first case study, we use the same airport data as Ferreira *et al.* (2010) but add some more, not only airport but also performance indicators, both chosen from the ATRS's (2009) publication, to produce an efficiency ranking of a set of worldwide airports using both the DEA and the MACBETH tool. In the second case study, we use data collected from a Portuguese airport, Madeira (FNC), on Madeira Island, from 2007 to 2011, to self-benchmark such an infrastructure using both the DEA and the MACBETH tool using the same performance indicators as in the previous case but also adding the number of closure hours per year due to natural (weather) effects.

5.1 Efficiency of a Set of Worldwide Airports

Ferreira *et al.* (2010) obtained an efficiency ranking of some worldwide airports, especially focused on Brazilian infrastructures, using a DEA approach. The authors used seven individual performance indicators to produce their ranking: four inputs (number of runways (RWS), number of aircraft parking positions (STANDS), passenger terminal area, m^2 (PAX TA), and cargo terminal area, m^2 (CARGO TA)) and three outputs (number of aircraft operations (MOVS), number of processed passengers (PAX) and cargo volumes, *tons* (CARGO)). After a review of the state-of-the-art literature as well as taking into account the opinions of some experts on airport benchmarking, we decided to add other inputs, namely the number of check-in desks (CHK-IN), number of boarding gates (GATES) and number of baggage belts (BELTS). Equally, we used some new airports, with a number of processed passengers higher than 19,000,000, as presented in the ATRS (2009) report. Thus, it was necessary to obtain the appropriate data, as presented in Table 2.

We used all these data to obtain an efficiency ranking based on the DEA and MACBETH approaches; note that if we had introduced these indicators as single ones within MACBETH, as mentioned, we would produce not an efficiency ranking but a performance one. Then, it was necessary to obtain new indicators, which we called complex ones, combining the above inputs and outputs, as suggested in Table 1. In that table, "movements" includes the number of aircraft landing at/taking off from the airport; "passengers" includes the number of passengers who arrive at and depart from the airport; and "cargo" includes the number of cargo tons that arrive at and depart from the airport, being domestic or international, freight or mail flights. Afterwards, we divided the work into two different parts to verify any position changes in the ranking due to the addition of new performance indicators: a) the DEA and MACBETH cases, which include the same inputs and outputs as those used by Ferreira *et al.* (2010); and the DEA+ and MACBETH+ cases, including all the performance indicators presented in Table 2, (Table 3).

Table 2. Airports Data

				Statistics 2011									
				INPUTS							OUTPUTS		
			IATA	RWS	STANDS	PAX TA	CARGO TA	CHK-IN	GATES	BELTS	MOVS	PAX	CARGO
South America	Brazil	Guarulhos	GRU	2	66	179790	64752	320	61	23	270600	30003428	515175
	Brazil	Galeão	GIG	2	53	280681	41800	150	50	15	139443	14952830	114097
	Brazil	Viracopos	VCP	1	11	8720	67458	70	9	4	99982	7568384	283267
	Brazil	Manaus	MAO	1	15	46266	9300	53	5	4	56298	3019426	179082
	Argentina	Aeroparque[1]	AEP	1	68	30000	10000	55	16	9	81675	5320292	13741
	Argentina	Ezeiza[2]	EZE	2	42	71000	203827	143	23	11	93346	8786807	248692
North America	Canada	Calgary	YYC	3	45	123000	54812	118	50	9	162000	12844523	116000
	Canada	Vancouver	YVR	3	108	255000	96200	250	95	14	296942	17032780	223878
	Canada	Toronto	YYZ	5	141	251054	84575	370	108	24	428477	33400000	492171
	Canada	Montreal[2]	YUL	3	64	72720	135000	208	60	13	217545	13660862	112000
	EUA	Tampa	TPA	3	75	174374	22300	116	59	14	191315	16732051	81822
	EUA	Atlanta	ATL	5	172	340955	130846	124	207	17	923991	84962851	638127
Asia - Pacific	Japan	Tokyo	NRT	2	141	783600	815580	584	67	28	183451	28068714	1898885
	Japan	Central Japan	NGO	1	66	220000	260000	180	28	9	82137	8890683	143134
	Singapore	Changi	SIN	2	85	650000	510000	444	92	15	301711	46543845	1865252
	Australia	Sydney	SYD	3	93	354000	53850	258	56	23	280910	35630549	249159
	China	Hong Kong	HKG	2	120	710000	351600	377	75	12	334000	53904000	3938000
	Dubai	Dubai	DXB	2	144	1444474	78600	400	82	31	326317	50980000	2190000
Europe	Germany	Munich	MUC	2	135	469400	58250	310	200	28	409956	37782256	303655
	Germany	Frankfurt	FRA	4	189	800000	90000	381	120	31	487162	56443657	2169304
	UK	Gatwick	LGW	1	115	258000	20300	348	94	16	244741	33639900	88214
	Serbia	Belgrade	BEG	1	22	40000	7300	47	16	4	44923	3124633	8025
	Italy	Milan	MXP	2	139	142000	45000	313	93	15	186780	19291427	440258
	Spain	Barcelona	BCN	3	168	674759	43692	258	149	28	303054	34398226	96572

[1] Statistics data for 2006, [2] Statistics data for 2010

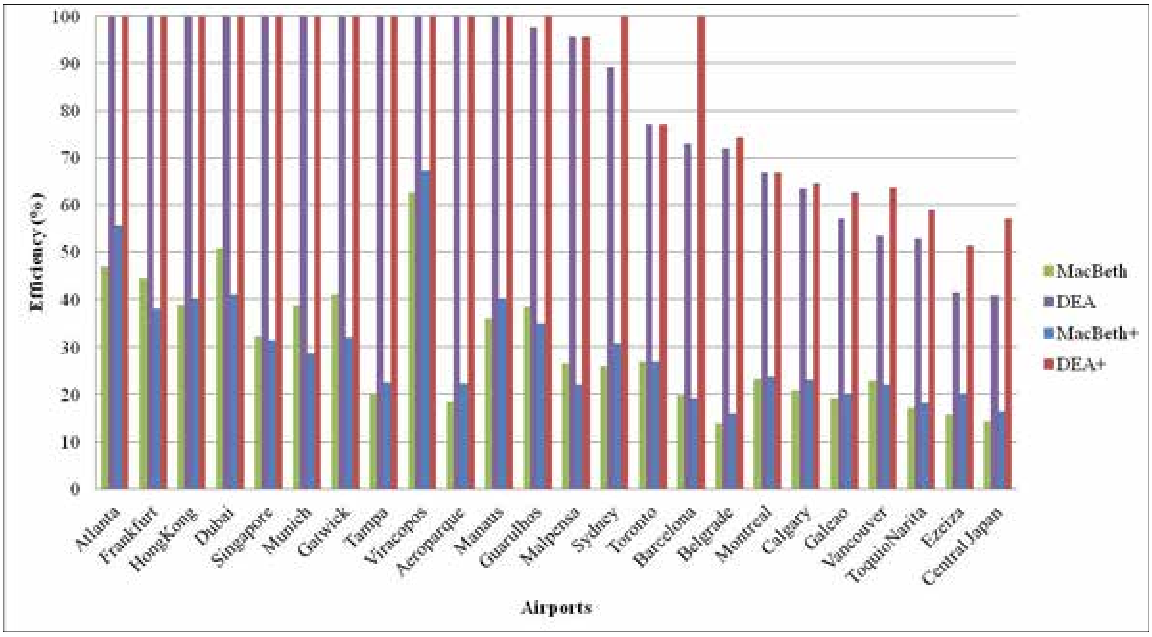
Source: Jardim, 2012

Table 3. Airports Position in the Efficiency Ranking for all the Case Studies

DMU	DEA efficiency (%)	DEA Rank	DEA+ efficiency (%)	DEA+ Rank	MACBETH efficiency (%)	MACBETH Rank	MACBETH+ efficiency (%)	MACBETH+ Rank
Atlanta	1	1	1	1	46,83	3	55,63	3
Frankfurt	1	1	1	1	44,32	4	37,80	5
Hong Kong	1	1	1	1	38,75	6	39,90	8
Dubai	1	1	1	1	50,61	2	40,95	2
Singapore	1	1	1	1	32,29	10	31,42	4
Munich	1	1	1	1	38,6	7	28,74	12
Gatwick	1	1	1	1	41,03	5	31,99	7
Tampa	1	1	1	1	20,15	17	22,42	17
Viracopos	1	1	1	1	62,51	1	67,19	1
Aeroparque	1	1	1	1	18,35	20	22,15	14
Manaus	1	1	1	1	35,77	9	40,14	6
Guarulhos	97,44	12	1	1	38,26	8	34,83	11
Malpensa	95,67	13	95,67	15	26,5	12	21,95	21
Sydney	89,05	14	1	1	25,85	13	30,76	9
Toronto	76,91	15	77,00	16	26,85	11	26,98	18
Barcelona	72,83	16	1	1	19,86	18	19,08	22
Belgrade	71,87	17	74,38	17	13,83	24	15,87	24
Montreal	66,87	18	66,87	18	23,32	14	23,93	10
Calgary	63,28	19	64,45	19	20,85	16	23,12	13
Galeao	57,05	20	62,53	21	19,16	19	19,91	16
Vancouver	53,29	21	63,48	20	22,81	15	22,09	15
Tokyo Narita	52,72	22	58,93	22	17,1	21	18,19	19
Ezeiza	41,38	23	51,39	24	15,79	22	20,05	20
Central Japan	40,68	24	56,95	23	14,39	23	16,26	23

Source: Authors

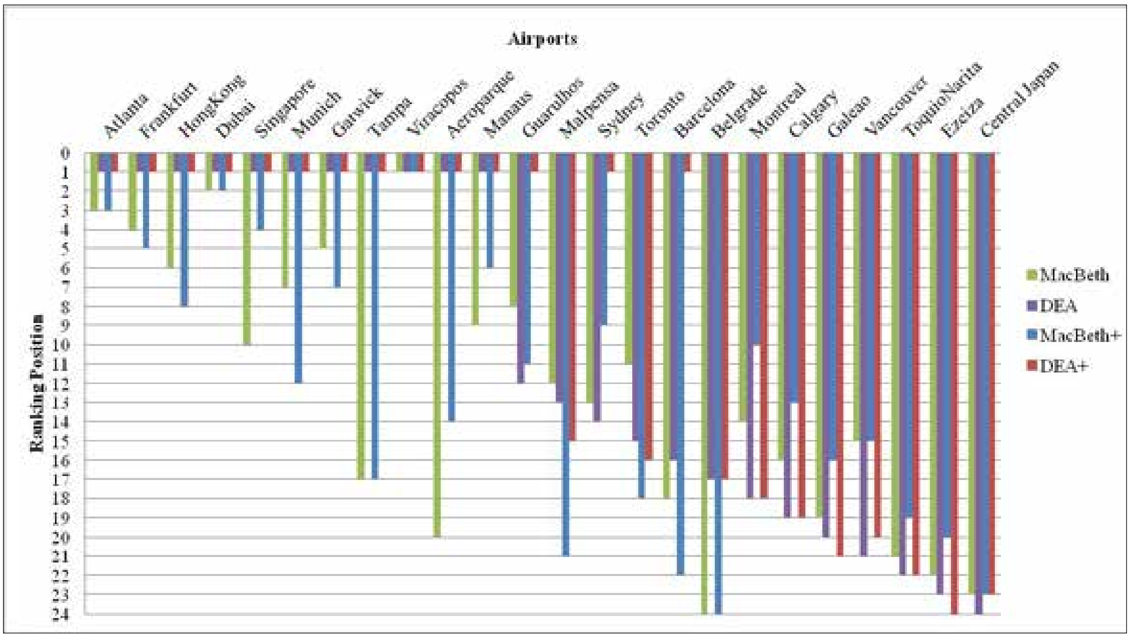
Figure 2. Comparative Efficiency for all Case Studies



Source: Authors

The efficiency rankings obtained following the DEA and MACBETH approaches are quite different. From Figure 2, it is possible to observe the variation in the efficiency rankings due to the use of the two tools. Indeed, the values of some airports differ between the approaches, since MACBETH follows a thinner approach (and presents a non-convergence one) and DEA presents more than one airport in the first place. Comparing the transition from DEA to DEA+, which represents the addition of new indicators, it is possible to observe that there are some similarities, such as for Atlanta, Dubai, Tampa, Viracopos and Frankfurt, but there are also great discrepancies, such as for Sidney and Barcelona. Comparing the transition from MACBETH to MACBETH+, which again represents the addition of new indicators, it is possible to observe that there are some similarities, such as for Atlanta, Dubai, Tampa, Viracopos, Belgrade, Vancouver and Central Japan, but also that there are great discrepancies, for example Singapore, Munich, Aeroparque, Malpensa and Toronto.

Figure 3. Comparative Ranking Positions for all Case Studies



Source: Authors

Figure 3 shows the comparisons between rankings, before and after the addition of new indicators, using either each tool with the same set of indicators (DEA and DEA+, and MACBETH and MACBETH+) or each set of indicators with each tool (DEA and MACBETH, and DEA+ and MACBETH+). It is possible not only to reach conclusions on the impact on some airports – such as Singapore and Malpensa – of the use of the MACBETH tool and on others – such as Guarulhos, Sidney and Barcelona – of the use of the DEA one, but also to determine that the addition of other, non-traditional indicators to the benchmarking study – such as check-in desks, boarding gates and baggage belts – has an important, non-negligible influence for some airports.

5.2 Self-Benchmarking for Madeira (FNC) Airport

An interesting improvement for benchmarking studies is the possibility of using both the DEA and the MACBETH tool to compare the efficiency values of a given airport over several years. This feature is particularly interesting when observing the answer given by the airport whenever there are investments in such infrastructure. If there are no investments, it is always possible to see how effective the airport has become over the years. Thus, this case study specifically undertakes the self-benchmarking of a Portuguese airport, Madeira (IATA code: FNC), on Madeira Island. We used the data from Table 4 as the input and output indicators.

Table 4. Madeira Airport Data 2007-2011

INPUTS									OUTPUTS		
DMU	RWS	STANDS	PAX TA	C TA	CHK-IN	GATES	BELTS	OP TIME	PAX	MOVS	CARGO
FNC2007	1	16	44590	4800	40	16	4	-[1]	2418489	21954	6774,6
FNC2008	1	16	44590	4800	40	16	4	-	2446924	22799	6637,6
FNC2009	1	16	44590	4800	40	16	4	-	2346649	21955	6228,4
FNC2010	1	16	44590	4800	40	16	4	-	2233524	22094	6069,5
FNC2011	1	16	44590	4800	40	16	4	-	2311380	21346	5095

[1] Data not available to be shown as requested by the airport authority.

Source: ANAM, 2007-2011

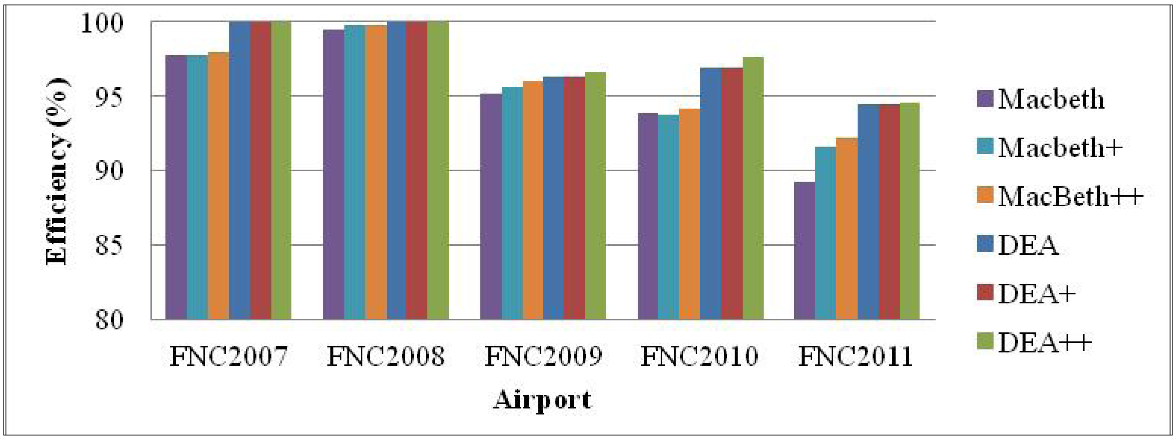
This case study is divided into three parts: in the first and second parts, the indicator structure is the same as that of the previous case study, as presented in Table 3, and the third one, which we called MACBETH++ and DEA++, corresponds to the inclusion of a new indicator related to the number of closure hours per year due to natural (weather) effects. As such **information** is **confidential**, as requested by the airport authority, the related data **cannot be displayed**; nevertheless, they were included in the case study. The purpose of these investigations was (again) to verify possible changes in the rankings, using both tools/methodologies, due to the addition of other performance indicators than the traditional ones. Thus, we used the MACBETH and DEA tools to rank Madeira Airport during a set of years, between 2007 and 2011. The weights for MACBETH and MACBETH+ are the same as those used previously, and for MACBETH++ they are (in accordance (again) with the opinion of the same 30 national and international aeronautical experts): MOVS/STANDS (15.63%), MOVS/RWS (11.80%), PAX/PAX TA (17.03%), CARGO/CARGO TA (11.96%), PAX/CHK-IN (9.96%), PAX/GATES (9.07%), MOVS/GATES (8.57%), MOVS/BELTS (8.11%) and OP TIME/TOTAL T (7.88%). The results are displayed in the following Table 5 and in Figures 4 and 5.

Table 5. Madeira Airport Positions in the Efficiency Rankings for the Five Case Studies/Years

DMU	DEA efficiency (%)	DEA Rank	DEA+ efficiency (%)	DEA+ Rank	DEA++ efficiency (%)	DEA++ Rank	McB efficiency (%)	McB Rank	McB+ efficiency (%)	McB+ Rank	McB++ efficiency (%)	McB++ Rank
FNC2007	1	1	1	1	1	1	97,76	2	97,77	2	97,95	2
FNC2008	1	1	1	1	1	1	99,47	1	99,73	1	99,74	1
FNC2009	96,29	4	96,29	4	96,64	4	95,19	3	95,61	3	95,92	3
FNC2010	96,90	3	96,90	3	97,60	3	93,81	4	93,73	4	94,15	4
FNC2011	94,46	5	94,46	5	94,50	5	89,21	5	91,54	5	92,20	5

Source: Authors

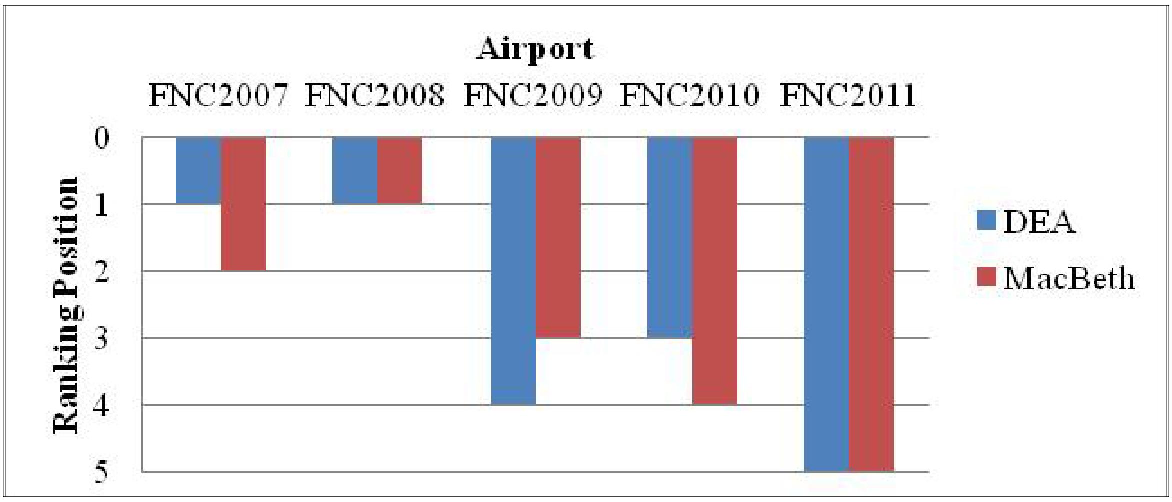
Figure 4. Comparative efficiency for all case studies



Source: Authors

Comparing on one hand MACBETH, MACBETH+ and MACBETH++ and on the other hand DEA, DEA+ and DEA++ (Figure 4), it is possible to observe that some differences exist in the efficiency values due to the successive addition of new indicators, despite no change existing in the rankings in each year and for each method (Figure 5). With the addition of new indicators, the efficiency values show a slight increase (Table 4), mainly with the inclusion of the closure time (even with the small weight/importance of 7.88% given by our experts). This fact is due to small changes in the closure times, each year, at the airport; however, we believe it to be an important indicator for measuring the airport's efficiency, mainly in some particular cases.

Figure 5. Balance between MACBETH and DEA Rankings



Source: Authors

As evidenced in Figure 5, the results obtained with the MACBETH and DEA approaches are quite different for 2007, 2009 and 2010. For both MACBETH and DEA, 2008 was the most efficient year for Madeira Airport and 2011 was the least efficient year.

6. FINAL REMARKS

MACBETH and DEA have the ability to compare either the airport with other similar infrastructures or the airport in different years, offering to all stakeholders the possibility to remain in touch with the evolution of the performance and efficiency of the infrastructure. The results obtained using the MACBETH tool are quite different from those obtained following the DEA approach, since MACBETH is a thinner approach and presents a non-convergence approach, as opposed to the DEA solutions. The natural/meteorological conditions under which airports are working seem to be, for our experts, not a relevant indicator to rank the infrastructure, either with others or with itself over time.

7. CONCLUSIONS

Benchmarking is a self-improvement tool for any organisation as it allows it to identify its own strengths and weaknesses, to compare itself with others and to learn more about how to improve its efficiency. There are several works on airport benchmarking, each using different performance indicators; some of them use single indicators, for example the number of aircraft parking positions, while others consider complex indicators, such as the number of passengers per area of the passenger terminal. It is easy to understand how important an MCDA approach is for airports' stakeholders to support the decision-making process. The main goal of this work is not only to balance the DEA and MCDA tools in general, but also to achieve airport rankings using a (new) multicriteria approach allowing a proper choice of both the indicators and the related weights. Therefore, we used MACBETH to rank airports in two ways, thus underlining the versatility of such a tool: the efficiency of a set of worldwide airports and the self-benchmarking of a Portuguese one (Madeira). The disadvantage of MACBETH in benchmarking airports is the subjectivity needed to determine the indicator weights, which can be mitigated in two ways: using the opinions of specialists in the appropriate fields of knowledge and obtaining as many answers as possible so that the related average (and variance) values are as close as possible to reality (Braz, 2011). The DEA analysis gives the indicator weighting by a mathematical approach, leading to some airports achieving the maximum efficiency simply because one indicator exists for that airport that is much better than the other ones. For this reason, this approach sometimes does not facilitate a clear understanding of the desired efficiency ranking.

The next research steps will be focused on using both the DEA and the MACBETH model, and the same efficiency indicators as used in the previous (+) cases, in benchmarking studies for: (a) the closest airports to the European Union capitals; (b) the most important Iberian airports (Portugal and Spain); and (c) the most important Portuguese ones. A further target is the self-benchmarking of some Iberian airports, including particular natural (weather) effects and ramp occurrences.

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