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PORTUGUESE AIRPORTS AND THEIR HINTERLAND: A GEOGRAPHICAL EFFICIENCY ANALYSIS USING ANALYTIC NETWORK PROCESS COMBINED WITH DATA ENVELOPMENT ANALYSIS

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Resumo

Os aeroportos e o seu *hinterland* encontram-se hoje em dia sob o foco de intensa investigação académica em termos de impactos económicos, sociais e ecológicos. Neste trabalho, visamos o estudo da eficiência geográfica dos aeroportos portugueses, usando para o efeito três Análises Envoltórias de Dados (DEA) com Rendimentos Variáveis à Escala (VRS), e uma ponderação das eficiências técnicas obtidas através do VRS DEA. Estes modelos são previamente apoiados por uma selecção de *inputs* e *outputs* com base nas prioridades definidas através do Processo Analítico de Rede (ANP). Observa-se que os aeroportos de Lisboa (continental) e de Santa Maria (ilha) se encontram na fronteira eficiente para todos os outputs seleccionados (com rendimentos constantes à escala). Sete aeroportos das ilhas obtêm resultados de eficiência técnica bastante bons, com especial destaque para Santa Maria, Corvo, Graciosa e Horta. O aeroporto de Faro obtém níveis de eficiência técnica especialmente baixos para os *outputs* número de destinos directos e volume de carga processada. Conclui-se que os aeroportos, ao contrário do que seria expectável, não sofrem de uma dissociação da eficiência consoante a sua localização geográfica, tipo de operação (Carga ou Passageiros) ou tamanho efectivo do aeroporto. Os aeroportos com uma função *Low Cost* apresentam resultados aquém dos obtidos para os aeroportos com operações ditas mais generalistas, por via do efeito do número de destinos.

Palavras-chave

Aeroportos; Portugal; DEA; ANP; Eficiência Geográfica; Hinterland; Rendimentos de Escala

Abstract

Airports and their hinterland are nowadays being the scope of academic research in terms of economic, social and ecological impacts. In this research we study the geographical efficiency of Portuguese airports, using to this purpose a Data Envelopment Analysis (DEA) with Variable Returns to Scale (VRS) and an average score of technical efficiencies obtained through VRS DEA. These models are previously supported by a selection of inputs and outputs based on the priorities of the Analytic Network Process (ANP). We observe that the airports of Lisbon (continental) and Santa Maria (island) are on the efficient frontier for all selected outputs (with constant returns to scale). Seven airports on the islands obtain quite good technical efficiency scores, with particular emphasis on Santa Maria, Corvo, Graciosa and Horta. Faro airport obtains very low levels of technical efficiency especially for the outputs 'number of direct destinations' and 'cargo volume'. We conclude that the efficiency of Portuguese airports, contrary to what may be expected, does not suffer from dissociations depending on geographic location, type of operation (cargo or passenger) or the effective size of the airport. Airports with a Low Cost function present results below those obtained by airports with more generalist operations, due the effect of the number of destinations technical efficiency scores.

Keywords

Airports; Portugal; DEA; ANP; Geographical Efficiency; Hinterland; Returns to Scale

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List of Acronyms

ANA	ANA Aeroportos, SA
ANAM	ANAM Aeroportos da Madeira, SA
ANP	Analytic Network Process
BCC	Banker, Charnes and Cooper
CCR	Charnes, Cooper and Rhodes
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DEAP	Data Envelopment Analysis Software
DMU	Decision-Making Unit
DRS	Decreasing Returns to Scale
GRETL	Econometrics Software
IGESPAR	Institute for Heritage Protection and Management
INE	National Institute of Statistics
IRS	Increasing Returns to Scale
LCC	Low-Cost Carriers
NUTS	Nomenclature of Territorial Units for Statistics
PE	Productive Efficiency
SATA	SATA Gestão de Aeródromos, SA
SE	Scale Efficiency
SREA	Regional Service of Statistics Azores
TAP	Transportes Aéreos Portugueses, SA
TE	Technical Efficiency
VRS	Variable Returns to Scale

PART I - INTRODUCTION AND LITERATURE REVIEW

1. INTRODUCTION

1.1. Context and Relevance of the Study

During the past thirty years, Airport's operators have ceased to be seen as simple providers of infrastructures due to an increase in the number and diversification of new related services. Thus far, plenty of benchmarking techniques have led the regulatory and operational sides of an airport further. Most of benchmarking techniques have been used to compare airports to best-in-class performers (Francis *et al*, 2002). This tendency has the merit of emphasizing the categorization of airports on the basis of operating performance as the main criterion. However, airports are also key levers for the development of a region, so they can no longer be managed in isolation from the geographical area they serve. Airport impacts pose actually considerable challenges for both airport operators and the surrounding urban and regional environment (Ferreira *et al*, 2006).

In fact, the valuable role of airports for a region goes far beyond providing high speed access for both business and leisure travellers. Nowadays, their ability to generate jobs and attract new business is being used in many locations as a justification for public investments in further airport construction and expansion (Weisbrod *et al*, 1993). Also, models of regional development have used airports at different levels; for example, in a tourism-oriented model of regional development, airports bring tourists and contribute conclusively for the success of the model (Adamaki-Tzavella *et al*., 2008).

There is, in fact, a consensus among researchers about the existence of benefits brought by the presence of an airport in a given region. Some of these benefits are measured as catalytic effects, being defined as the net economic effects (e.g., on employment, incomes, and government finances) resulting from the contribution of air transport to tourism and trade and its long-run contribution to productivity and gross domestic product (GDP) (TRB, 2007). Furthermore, geographical constraints of airports may support the definition of individual strategies, in order to unleash their full potential (Tapiador *et al*, 2008).

Airports are no longer exclusive to the most developed regions. Their location and size is a strategic factor of equity among regions, notably for policy makers with concerns about regional development.

In fact, the thematic of regional development gives great importance to transport infrastructures, namely airports. Like other transport infrastructures, airports have very high sunk costs and may be subject to several expansions and maintenance works. Still, the construction of an airport may become the catalyst for a region's development, because it assumes a strong role enabling the raise of the Gross Regional Product. Even so, some factors need to take place simultaneously to ensure the contribution of airports to a region's growth, namely:

- The creation of a good infrastructure network for the airport's supply chain;
- The need and achievement of an increasing mobility of the population;
- The entry in a market regulated by governments and aviation regulation agencies, and the competition with established airports;
- Acceptable levels of noise and pollution, compatible with the population's quality of life prior to the airport's construction;
- The existence of more inbound tourism than outbound tourism, in order to preserve a balanced regional growth;
- The overall economic performance of the region.

Airports, given a certain scale, develop a strong time-saver role for firms requiring quick shipping, or quick business meetings, being able to put their merchandise and businessmen all over the world in a matter of hours. The benefits generated with the presence of the airport will, in turn, create spin-off-effects called 'catalytic effects' or 'transportation benefits', which will impact tourism, trade, investments on the airport or region, and productivity generated by industries, which may not work directly with the airport (Malina *et al.*, 2008).

Notwithstanding all these assumptions, we believe that the importance of airports to regional development can also be seen as the result of hinterland influence on the operational activity of airports. In this context, Tapiador *et al* (2008:208) follow a complementary approach and use the term "geographical efficiency" to refer to how efficiently an airport benefits from its location. Like Tapiador, we assume that "this geographical efficiency is linked to certain key characteristics of the size of an airport's catchment area, such as population, level of economic activity, accessibility or tourism potential. Some of these variables, such as population, are linked with the traffic from the airport, whereas others, such as the tourism potential, account for potential trips to the airports." We propose a new methodology for the evaluation of airports' geographical efficiency based on Analytic Network Process (ANP) and Data Envelopment Analysis (DEA).

Our empirical study is based on the work of Tapiador *et al.* (2008), who proposed a new variant of efficiency assessment in airports. Tapiador analysed the efficiency of Spain's airports through the application of a geographic variant of DEA instead of the more common operational indicators. The method was also applied by Hájek and Grebeníček (2010) to assess the geographical efficiency of Czech regional airports.

Distinct from these works, our study uses a DEA-ANP combination as a method for assessing the geographical efficiency of airports, applying it to the Portuguese Airports.
As far as we know, the ANP method is applied for the first time to Portuguese airports studies. Also the present work adds geography to Portuguese airports benchmarking from a territorial policy view, thereby strengthening the role played by secondary airports within their respective regional economies (Tapiador *et al*, 2008).

1.2 Research questions and objectives

As stated before we assume that airports perform differently according not only to operational aspects (such as employees, size of terminal or number of gates), but also according to the inputs they use or might use from their hinterland.

But a question arises: does the airport effectively take benefits from its hinterland resources? The inverse question can also be asked, leading to a scenario where the benefits that the airport takes from its hinterland can generate, by their turn, benefits to the region, creating positive feedback loops and causality relationships which are very challenging to model and determine. A possible approach to answer to this question lies in evaluating if airports are operating efficiently according to the resources they have in their hinterland.

This approach leads to the **main questions** of the present study:

1. Is the operational efficiency of airports affected by the distinctive features of their hinterland?
2. To what extent the resources and characteristics of the hinterland contribute to operational efficiency of airports?

The answers to these two questions support the **main objective** of this research, which is: **to assess the geographical efficiency of Portuguese airports based on a variable selection model oriented to the different characteristics of the airports' hinterland, trying to identify possible significant differences between these airports.**

Consequently, the best inputs and outputs must be selected to measure the geographical efficiency of Portuguese airports and the variables they are served by. The specification of the inputs is made possible using the ANP, a Multi-Criteria Decision-Making (MCDM) tool.

1.3 Structure of the research

This work is structured in two parts, each one subdivided in several chapters.

The first part, besides the introduction (Chapter 1), is related to the review of literature. Thus, the theoretical framework is first defined with the identification of relationships between airport and regional development (Chapter 2). Benchmarking theories and applications are explored to select the best suiting methodology for our study (Chapter 3). Finally, DEA (Chapter 4) and the multi-criteria decision methods like AHP and ANP models (Chapter 5) are explained and adapted to our study.

The second part is related to the empirical study. In addition to the objectives and methodology of the empirical research (Chapter 6) the Portuguese airports and their hinterland are presented and characterized (Chapter 7). After, an ANP model for hinterland variables selection is displayed, as well as a synthesis of the results (Chapter 8), which are used for the DEA efficiency estimations (Chapter 9). The discussion of the empirical results (Chapter 10) precedes the last chapter (Chapter 11), where we present the final conclusions, limitations of the study and some recommendations.

2. AIRPORTS AND REGIONAL DEVELOPMENT

Rietveld (1989:255) provides a good definition of the importance of infrastructures, of any kind, on regional development:

"Regional development is not only the result of private production factors such as labour and capital but also of infrastructure. Improving infrastructure leads to a higher productivity of private production factors. Conversely, a neglect of infrastructure leads to a low productivity of the other production factors."

Relatively to the specific nature of transport infrastructures, which are extensively said to be catalysts of regional development, Izquierdo (1997) argues that the infrastructure by itself does not generate economic development in general, neither regional development. Still, infrastructures may act as catalysts in the promotion of development benefiting from their location (European Investment Bank, 1998). Location theorists as early as von Thünen (1826) noticed that, because of the variation of transportation costs and economic rents across goods, the land uses and its use intensities will differ as we get farther from the marketplace.

Nevertheless, few have studied the effects of the airports on regional development, nor the effects of regional development on airports (Green, 2007). Brüeckner (2003) and Green (2007), applied OLS regressions to airport activity at airports' metropolitan area to predict population and employment. Ferreira *et al*. (2006) argued that airports and their surrounding commercial districts are playing an increasingly important role in shaping urban and regional growth patterns, defining "airfront" as the spreading range of commercial, industrial, and transportation facilities intrinsically tied to the airport.

Since airports are no longer exclusive to the most developed regions, their location and size is a strategic factor of equity among regions, notably for policy makers with concerns about regional development. Nevertheless, regional airports can also promote regional diseconomies, for example, if passengers mostly make tourism abroad, namely if the airport clearly supports low-cost carriers (Stewart, 2009). Low-cost carriers are also bringing a great downward pressure to aviation revenues of airports (Martens and van der Zwan, 2011), causing a shift from aviation to non-aviation revenues.

For Weisbrod *et al*. (1993), hubs/international airports should have more freight activities, whereas passenger and business-oriented airports should have more hotels and business in the vicinity. Weisbrod confirmed the tendency for airports to generate jobs and attracting new businesses, using this argument as a justification for public investments in new airport construction and expansion, but also argued that business could take up to 20 years to develop activities in the surrounding land of the airport.

Malina *et al*. (2008) estimated the benefits of the presence of an airport for business as the willingness to accept a fee for the closure of an airport.

The Transportation Research Board (TRB, 2008) argues that airports exert significant effects on regional demand, estimating the effects on value added, employment, income, and tax revenue that result from economic activities taking place at the airport:

- Companies at the airport site (the airport operator, airlines, ground handling companies, retailers etc.) are generally important regional employers; they produce goods and services for which they need intermediate and capital goods, thus increasing regional demand;
- Employees of companies at the airport site and of producers of capital and intermediate goods spend part of their income within the region, also creating additional demand.

3. THE IMPORTANCE OF BENCHMARKING AND ITS APPLICATIONS TO AIRPORTS

Benchmarking is one of the most performed practices nowadays. The benchmarking process usually identifies the best performer in a given amount of performers, where there is possibility of drawing comparisons. This requires a similarity in the structure of the performers and their practices. Then, the results and processes of the performers studied are compared with others, allowing the identification of the best practices.

Benchmarking is valuable for three reasons: it provides basic data otherwise difficult to obtain, defines world class standards for facilities, and identifies priorities for improving the physical design at individual airports. Effective benchmarking thus focuses on objective data of capacity or performance that can be measured and observed across widely different operations, rather than on data that is either subjective derived from widely different accounting practices (Neufville and Guzmán, 1998).

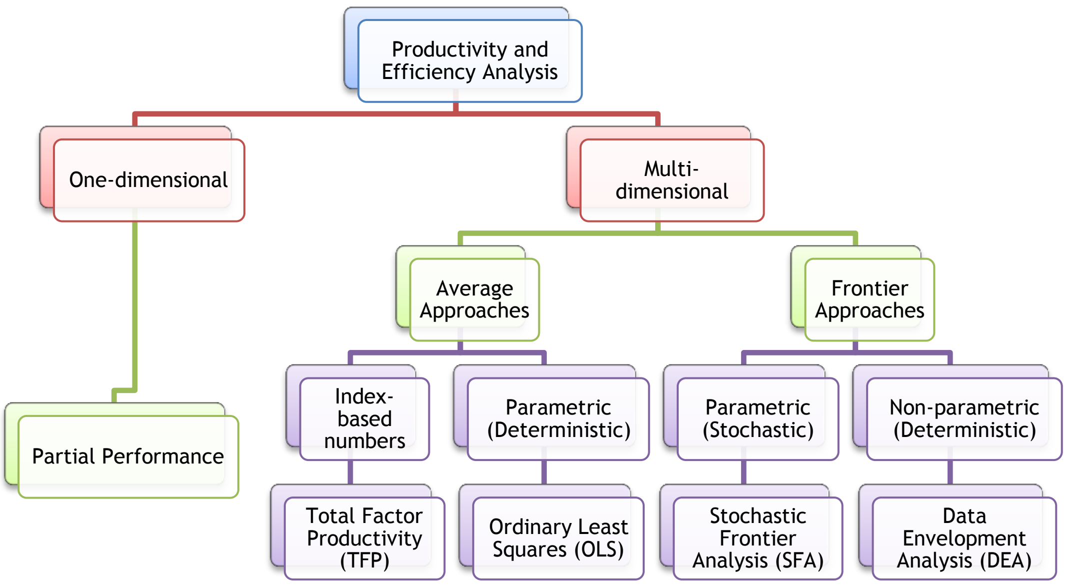
In the aviation sector, benchmarking analysis is considered as one of the ways to drive airports towards the frontier of best practices (De Borger *et al*., 2002, cited in Barros and Dieke, 2007:184). Graham (2005) identified airlines as one of the most interested parties in the benchmarking of airports, because they design their routes taking into account the selection of the most efficient airports. Graham also discussed the interest of government regulators of airports when establishing or reviewing the regulations which they set, and investors and bankers which are interested in airport privatization may want to use benchmarking techniques to identify possible business opportunities.

The Airports Council International (ACI, 2006) divides two general types of benchmarking:

- Partial - assessing and comparing individual processes/functions/services;
- Holistic - creating a systematic approach for defining and assessing a critical set of processes/functions/services that, when taken together, indicate the relative performance of the total organization.

A common distinction in benchmarking is to treat the process as internal, self-benchmarking within an organization which compares internal performance of processes/functions/services over time (time-series), or external, which compares performance across organizations with peers or in other industries (cross-sectional) at a single point in time and through time (ACI, 2006). Von Hirschhausen and Cullmand (2006), quoted by Liebert *et al*, 2010:24) identified the main methodologies used for airport benchmarking, which are depicted in Figure 1.

Figure 1 - Methodologies for Airport Benchmarking



Source: Adapted from von Hirschhausen and Cullmand (2006, *in* Liebert *et al*, 2010:24)

These methods have all different applications which are convenient to distinguish. According to Hensher and Waters (1993), the main methods to generate comprehensive performance measures of efficiency are the following:

- Non-parametric index number;
- Parametric model estimation (OLS or SFA);
- Non-parametric estimation (DEA).

Moreover, Kincaid and Tretheway (2009) provided a comprehensive table (see table 1) of the purposes of airport benchmarking, the types of measure used, level of “aggregation” and "comparators" of the studies, which are important for the categorization of our airport benchmarking study.

Table 1 - Use of Benchmarking

Purpose	Types of Measure	Level of Aggregation	Comparators
Assess Performance	• Price • Customer satisfaction • Service quality • Unit cost • Efficiency	Airport or individual services	• Best in class • Natural competitors
Collaborative benchmarking	• Price • Customer satisfaction • Service quality • Unit cost • Efficiency	Airport or individual services	Other group members
Price regulation	Efficiency	Airport	Best in class or peer airports
Assess Policy	• Price • Service quality • Unit cost • Efficiency • Investment • Throughput or take-up	National or airport	**To inform policy:** • Best in class • Competitor countries • Countries that have major policy reform **To assess policy outcomes:** • Control group of countries that have not enacted policy changes

Source: adapted from Kincaid and Tretheway (2009)

Our study inserts itself in the assessment of airport efficiency category, since it is the main object of benchmarking research, taking the best in class comparator.

4. DATA ENVELOPMENT ANALYSIS (DEA)

The application of operations research to the aviation field has been greatly expanded in the last years, mainly due to the increase in the capability of constructing non-parametric models and the increasing availability of variables. DEA has been applied extensively to measure relative efficiencies in a given set of decision-making units (such us airports), involving homogenous datasets of variables for each unit (Ulutas and Ulutas, 2009).

Table 2 joins authors who focused their studies on the use of DEA to measure the operational efficiency of airports:

Table 2 – Review of Literature on DEA

Seiford (1997)	Did a DEA literature bibliography review for the years 1978-1996.
Tavares (2002)	Reviewed 3203 studies for the period 1978-2001.
Schaar and Sherry (2008)	Examined the difference between results in DEA studies, coming to the conclusion that, following the model used, results would change in small, medium and large scale airports. The efficiency in CCR models tended to degrade from small to medium to large scale airports, whereas in SBM models efficiency tended to degrade from large to medium to small scale airports, and BCC models showed

	no tendency.
Humphreys and Francis (2002, cited in Barros and Dieke, 2008:1041)	Said "While there is extensive literature with DEA applied to a diverse range of economic fields, the scarcity of studies regarding European airports bears testimony to the fact that this is a relatively under-researched topic".
Graham (2005)	Investigated DEA and TFP and identified that the key advantage of DEA facing TFP is that the weights for the inputs and outputs are not pre-determined but instead are the result of the linear programming procedure. DEA is therefore a more attractive technique than the other methods because it has less demanding data requirements.
Barros and Dieke (2008)	Collected several studies related to the benchmarking of airports through DEA, using the Simar and Wilson (2007) two-stage. They observed that there is a tradition of analysing airports by separating activities into terminals and movements (Gillen and Lall, 2001, Pels *et al.*, 2001 and Pels et al., 2003). They also observed that several papers compare the DEA model with the frontier model (Hooper and Hensher, 1997, Pels et al., 2001, 2003), while a few others combine principal component analysis with a DEA model (Adler and Berechman, 2001), or focus on stochastic frontier analysis to assess the airport's efficiency (Pels *et al.*, 2001, 2003).
Pavlyuk (2012)	Made an extensive review of the airport benchmarking theory and applications, namely the airport business model and all the benchmarking techniques used in the studies covered by his survey, and the spatial competition among airports.

Source: own elaboration

Many academics encountered a number of difficulties in attempting to benchmark the airports and identify the best performers in the airport sector; these difficulties arise from differences in accounting and regulatory regimes, which are subject to different ownerships and policies of airport operators, and the degree of vertical integration (Müller et al., 2009). Moreover, agents such as airlines can bring many barriers with tariffs and the access to the airport for other airlines.

DEA is an input-output tool coming from the operations research field, which focus on benchmarking efficiency through the modelling of convexities and, therefore, has not the capability to study the catalytic impact of an airport to the surrounding economy.
Still, some of the spill over effects can be contended if the geographical effect of efficiency is considered and best practice cases are compared with less efficient ones.

DEA deeply takes roots in the work of Farrell (1957). Farrell argued that the efficiency of a single firm (or unit) consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximum output from a given set of inputs, and allocative efficiency, which reflects the ability of the firm to use optimal proportions, given their respective prices and production technology. These two measures are combined to provide a measure of total economic efficiency.

This work was later revised and consolidated in 1978 with the PhD thesis of Rhodes, under Cooper's advisement, as quoted by Casa Nova and Santos (2008:135), which aimed at the technical efficiency benchmarking of a program performance for necessitous students in several schools, based on the Farrell input-output premise, whether schools adopted the program or not. Charnes *et al*. (1978) finally computed a non-parametric procedure that compares a decision unit with an efficient frontier using performance indicators.

The model improved and resulted in the DEA CCR model (Charnes *et al*, 1978), published in the European Journal of Operations Research during the same year, which extends the single-input, single-output ratio measure of the efficiency of a single Decision-Making Units (DMU) proposed by Farrell to a multiple-inputs, multiple-outputs efficiency measurement. The premise of the CCR model is to compare the technical efficiency among DMUs, presenting which of the DMU is the most efficient by comparison to other DMUs. Cooper *et al*. (2003) define full (100%) efficiency as the maximal efficiency attained by any DMU if, and only if, none of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

4.1 The CCR model

The CCR model is limited by constant returns to scale (CRS). This means that there is no assumption that any positive or negative economies of scale exist, and, as such, a small airport should be able to operate as efficiently as a large one (Schaar and Sherry, 2008). The input-oriented CCR model is generally presented as follows:

$$Max\ h_k = \sum_{r=1}^{s} u_y\, y_{rk} \quad (1.1)$$

Subject to:

$$\sum_{i=1}^{m} v_i y_{rj} - \sum_{i=1}^{n} v_i x_{ij} \leq 0 \quad (1.2)$$

$$\sum_{i=1}^{n} v_i x_{ik} = 1 \quad (1.3)$$

$$u_r, v_i \geq 0$$

$y_r = amount\ of\ output\ r;\ \ x_i = amount\ of\ input\ i;$

$u, v = weights$

$r = 1, \dots, m;\ \ i = 1, \dots, n;\ \ j = 1, \dots, N$

Solving the linear programming problem for each DMU, the most efficient DMUs are identified. Relative efficiencies between DMUs can be obtained solving the problem for each DMU.

4.2 The BCC model

Banker *et al* (1984) developed a new DEA model with variable returns to scale (VRS), also called BCC model. The input-oriented BCC model is usually written this way:

$$Max \sum_{r=1}^{s} u_r\, y_{rk} - u_k \quad (2.1)$$

Subject to:

$$\sum_{i=1}^{n} v_i x_{ik} = 1 \quad (2.2)$$

$$\sum_{i=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} - u_k \leq 0 \quad (2.3)$$

$$u_r, v_i \geq 0$$

$y_r = amount\ of\ output\ r;\ \ x_i = amount\ of\ input\ i;$

$u, v = weights$

$r = 1, \dots, m;\ \ i = 1, \dots, n;\ \ j = 1, \dots, N$

The CCR and BCC models present different convexity areas, due to the introduction of the u_k variable in the equation (2.1) (Casa Nova and Santos, 2008). Consequently, the efficiency indicator of the BCC model is less or equal to the CCR model efficiency indicator (Belloni, 2000) and represents a measure of Technical Efficiency rather than Productive Efficiency, due to the clearance of production scale effects in the BCC model (Casa Nova and Santos, 2008).

The relationship between indicators of both models allows extracting another measure of efficiency called Scale Efficiency (Banker *et al*, 1984), which results from equation (3). This efficiency enables us to identify differences in the operation of small-scale by comparison to bigger airports.

$$SE(x_k, y_k) = \frac{PE(x_k, y_k)}{TE(x_k, y_k)} \quad (3)$$

Where:

$$SE(x_k, y_k) = Scale\ Efficiency$$
$$PE(x_k, y_k) = Productive\ Efficiency$$
$$TE(x_k, y_k) = Technical\ Efficiency$$

A DMU has to be simultaneously scale efficient and purely technical efficient to be considered CCR-efficient, or productive efficient (PE), whether it only has to be purely technical efficient (TE) to be considered BCC-efficient. Thus, the ratio of *CCR-efficiency/BCC-efficiency* is equal to equation (3) and gives us the Scale Efficiency.

Put in practice, the scale efficiency enables us to study with more detail if airports are operating well according to their size.

4.3 Limitations

However, like any empirical technique, DEA is based on a number of simplifying assumptions that are well known among the academic community and are commonly acknowledged when interpreting the results of DEA studies (Seiford and Thrall, 1990):

- Being a deterministic rather than statistical technique, DEA produces results which are particularly sensitive to measurement error. DEA only measures efficiency relative to best practice within the particular sample. Thus, it is not meaningful to compare the scores between two different studies;
- DEA scores are sensitive to input and output specification and the size of the sample;
- DEA does not perform full-ranking; instead, it merely provides classification into two dichotomic groups: efficient and inefficient (Royendegh and Erol, 2009);
- The number of efficient firms on the frontier tends to increase with the number of inputs and output variables (Berg 2010).

Furthermore, DEA determines the indicator weights by mathematical approach. Several airports can be pointed as fully efficiency simply because it exists at least one indicator on those airports which is much better that the others, leading at times to an unclear understanding of the efficiency ranking (Braz *et al.*, 2012). This is also known as the "Convergence" problem, since the efficiency of DMUs will converge to 1 (maximal efficiency).

Because of this limitation, and in order to preserve a good balance between DMUs and variables, in our study an ANP model is structured to select the best variables.

5. MULTI-CRITERIA DECISION METHODS: THE AHP AND THE ANP

Multiple-Criteria Decision Methods (MCDM) are methods used in situations where one or more criteria (e.g. cost, revenue, quality) are considered, working with a common tool named Decision Matrix, to analyse priority among given alternatives. MCDM provide useful information to decision-makers for many reasons (Braz *et al*, 2012):

- Enabling multiple stakeholder preferences to be modelled;
- Offering improved coordination and collaboration;
- Implementing the integration of spatial information.

The adoption of a MCDM in our study is justified with the need of selecting the best indicators among a given set, based on a given number of criteria. Although the problem is relatively well-known among DEA users, we found no study indicating ideal ratios between DMUs and inputs/outputs. We propose a model with 3:1 of proportionality between DMUs

(Airports) and variables (Inputs and Outputs) to avoid obtaining too many efficient units on the frontier.

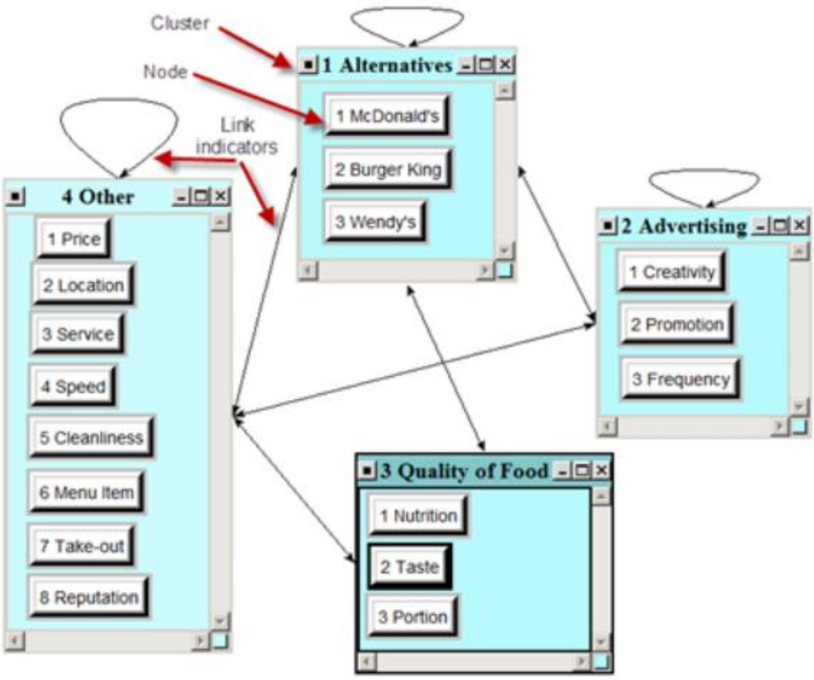
5.1 Analytic Hierarchy Process (AHP)

The ‘Analytic Hierarchy Process’ (AHP) was proposed by Saaty (1977) to model subjective decision-making problems in a hierarchical structure of goals, criteria, sub criteria and alternatives, respectively. AHP is based on pairwise comparisons between criteria and alternatives in a structured manner, in order to rank alternatives according to the answers of the decision-maker. This assumes that the decision maker can provide paired comparisons based on his knowledge and intuition. The applications of AHP can refer to corporate planning, portfolios election, and benefit/cost analysis by government agencies for resource allocation purposes.

5.2 Analytic Network Process (ANP)

The ANP (Saaty, 1996) is a generalization of the AHP, which tries to solve the independence constraint among elements in the same hierarchical level present in AHP. A network is composed of clusters, nodes and links among the nodes. Although the AHP has been introduced in the decision-making literature earlier, the AHP is a specific ANP model; hierarchies are special cases of networks in which the links point from the goal to the criteria to the alternatives. The ANP also allows an evaluation of the relative importance of its various elements by pairwise comparisons. AHP and ANP convert these evaluations to numerical values (weights or priorities), which are used to calculate a score for each alternative (Saaty, 1980). A consistency index measures the extent to which the decision-maker has been consistent in his responses.

Figure 2 – An example of an ANP Model for the estimation of market share



Source: Super Decisions Software (demonstration model)

All concepts highlighted with a red arrow (link indicators, nodes and clusters) in Figure 2 are fundamental to understand how the model is built. The link indicators are the interactions and feedback within clusters and between clusters.

ANP provides a thorough framework that includes clusters of elements connected in any desired way to investigate the process of deriving ratio scales priorities form the distribution of influence among elements and among clusters (Saaty, 2001). Feedback can better capture the complex effects of interplay in human society.

The next step in an ANP problem is to form the networks. Then, for each network corresponding to one of the several control criteria under benefits, the priorities from paired comparison matrices are derived, and are used in super matrix. The control criteria and decision networks for input alternatives are formed. Table 3 represents the values that pairwise comparisons take with respect to a given criteria.

Table 3 - The fundamental scale of the AHP and ANP

Intensity of importance	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one element over another
5	Strong importance	Experience and judgment strongly favour one element over another
7	Very strong importance	An activity is favoured very strongly over another
9	Absolute importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Used to express intermediate	

	values	
Decimals	1.1, 1.2, 1.3, …1.9	For comparing elements that are very close
Rational numbers	Ratios arising from the scale above that may be greater than 9	These ratios are used to complete the matrix if consistency were to be forced based on an initial set of n numerical values

Source: adapted from Super Decisions

While ANP is a more general form of the Analytic Hierarchy Process (AHP), used in Multi-Criteria Decision Analysis (MCDA), literature shows little difference in the applications of these methods, but the ANP allows a more in-depth a thorough analysis, enabling more complex relationships and a higher degree of adjustment to real life problems. Furthermore, the ANP allows the existence of dependency between alternatives and criteria, and their inclusion in clusters.

AHP has been applied successfully as a MCDA tool to airports, namely by Vreeker *et al.* (2001), evaluating airports expansions plans. Some authors applied the ANP for risk management. For example Yilmaz (2008) developed a model for airline risk management and Chen et al. (2011) developed an Environmental Risk Management model. Tsai and Kuo (2011) evaluated the airport service quality through a hybrid MCDM approach containing an ANP model.

5.3 AHP, ANP and DEA Combinations

The combination of AHP and DEA is not new, and there have been several attempts for using them in the present (Royendegh and Erol, 2008). Still, the combination of ANP and DEA is under-researched.

Royendegh and Erol (2008) recommend a DEA-ANP hybrid algorithm in order to eliminate both the ordering in the DEA model and the disadvantage of the whole hierarchy and subjective evaluations in the ANP method. Ulutas and Ulutas (2009) measured the efficiency of Turkish airports through a combined ANP-DEA model, where the ANP is used to determine the best inputs to enter the analysis. This combined analysis was pioneered by Sarkis (1999), involving the synthesis of ANP and DEA for environmentally conscious manufacturing programs. Hasan *et al.* (2008) also integrated ANP and DEA, but in a multi phased supplier selection approach.

AHP and ANP have also been combined *a posteriori* with DEA to provide efficiency rankings. Those methods are called DEAHP or DEANP according to the type of the analytic model. Research on improving and doing combinations of these methods is still on-going, as well as their issues and applications (*e.g.* Ramanathan, 2006; Wang and Chin, 2008; Davoodi *et al*, 2012; Kejia and Xiankang, 2011). Examples of these applications include integrated DEAHP and DEANP into the Quality Function Deployment (QFD) (Kamvysi *et al.*, 2010).

Through the combination DEA-ANP as a method for assessing the regional efficiency of airports, our study contributes to the literature on regional/geographical analysis and airports benchmarking.

PART II - EMPIRICAL STUDY

6. OBJECTIVES AND METHODOLOGY

6.1 Objectives of the Empirical Study

The main objective of the empirical study is to assess the geographical efficiency of Portuguese airports, while setting up a new procedure for geographical efficiency analysis. To do this, we first provide a definition and characterization of airport operators, and then we select the variables according to their relative importance with respect to location and other criteria further explained in the ANP model chapter.

The next step is providing good results from DEA and discussing them. We elaborate efficiency rankings according to the outputs selected, and we create an overall technical efficiency scorecard, to avoid the limitations of multi-output DEA estimations.

6.2 Methodology

To do a comprehensive comparison of airports, the best-in class comparison approach allowed by DEA is used. Based on our literature review of Benchmarking, the DEA best-in class approach is preferable for four main reasons:

- Airports are ranked by comparison with their peers and not by their individual performance;
- Airports have generally the same kind of inputs to generate their activity;
- Airports can be ranked even if performing at different scales;
- The data requirements are less time and money demanding than other methodologies such as catalytic impact studies or econometric regressions.

This study approaches the efficiency of Portuguese airports in a procedure similar to the one used by Tapiador *et al.* (2008), who related the resources present in the hinterland of each airport with the volume of passengers carried at that time, allowing them to identify which resources were fully exploited and which remained underexploited. They pointed out many benefit of this analysis, mainly:

- To link territorial policies to the needs of airports;
- To point the criteria that Low Cost Carriers (LCCs) use to select new airport destinations;

- To identify and conceptualize geographical constraints.

The volume of passengers carried by each airport is a potent instrument to predict or explain regional growth, as proved by Brüeckner (2003) and Green (2007), who found that passenger activity is a powerful predictor of population growth, whether cargo activity is not (Green, 2007).

In this context, the scale efficiency present in geographical study done by Tapiador *et al*. is of extreme relevance to determine which airports are operating according to their hinterland potentials.

Furthermore, some regional airports located in islands are characterized by strong tourist traffic with seasonal demand. The efficiency of these airports directly affects the quality of service offered to passengers who use it as a basic means of transport to reach their destination (Psaraki and Kalakou, 2010).

Regarding the study of Tapiador *et al* (2008), our study differs because we introduce the ANP model to select the best variables before entering DEA. This aims to overcome the following limitations:

- The convergence problem of inputs of a DEA model with few airports (Braz *et al*, 2012);
- The lack of homogeneity among the studied airports, or Decision-making Units (DMUs).

Once determined which inputs enter the dataset, DEA will enable us to measure the efficiency of our set of airports. Taking an operational approach in geographical/regional efficiency analysis permits to determine wastes in less efficient airports, to help predicting regional development, and to support decision making in urban planning policy.

The hinterland appeared as a term initially applied to the background of seaports. With the development of hinterland studies, the terminology separated into importer hinterland and exporter hinterland, depending on the source / destination of the goods.

In the context of airports and human geography, the term Catchment Area is a more widely used term, which corresponds to the area and population from which a city or individual service may attract visitors or customers, but still diverges from the definition of Hinterland as a provider of resources and not only a static area in the neighbourhood of the airport. Nonetheless, the catchment area proves to be a good starting point to define what has to be included or excluded from Portuguese airports' surrounding area, and which variables are going to be selected.

Postorino (2010) defines the 'Catchment Area' as the area containing all the potential users and passengers of a given airport, from a geographical point of view. The later also defends that accessibility is the key to development and particularly for airports, as he relates a larger catchment area with a larger potential demand.

The size of the Catchment Area is of very high importance for passengers to choose an airport, when there are competitors within the same range. The Catchment Areas can be usually defined in two ways:

1. Formation around boundaries (districts) based on government regulation or other spatial assumptions.
2. Population living, as a general rule of thumb, in a time of 2 hours by bus, car or train to the airport.

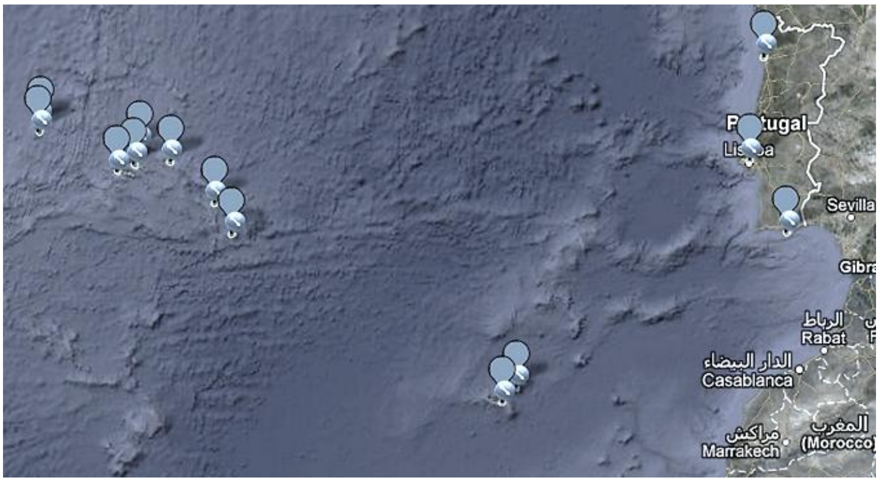
We use the first definition, since we keep the hinterland to the district (when the airport is continental) or island level, because of the difficulty to compare areas of influence. We select a sample of 14 Portuguese airports with regular routes and available data collected from INE, SREA, ANA, SATA, and IGESPAR for the 2008-2010 period (2005 for IGESPAR). Other small regional airports do exist (notably the regional airports of Bragança, Évora, Vila Real and Tires), but could not be integrated in this list, since no disaggregated information is available for the years under study. For the treatment of the data we used the software's implementations of ANP and DEA for PC, which are respectively called Super Decisions and DEAP v2.1.

7. PORTUGUESE AIRPORTS AND THEIR HINTERLAND

7.1 Presentation of the Portuguese airports

We study a heterogeneous group of fourteen airports, where nine are controlled by two State-owned companies (ANA Aeroportos, S.A. and its subsidiary ANAM, S.A. in the Madeira archipelago), four smaller airports in the Azores by a regional public company (SATA Gestão de Aeródromos, S.A.) and the "Aerogare Civil das Lajes" being owned and operated by the Azores Regional Government. Nine airports are located in the Azores Islands, two in the Madeira Islands, and three in the continent.

Figure 3 - The 14 studied Portuguese Airports



Source: Google Earth Software

7.2 Brief characterization of the Portuguese airports and their hinterland

A primary ranking of the Portuguese airports (including the islands) is made according to the article 2005/C 312/01 of the European Commission[1], which categorizes the airports according to their passenger Volume. In table 4 we also join the operational indicators available for each airport.

Table 4 – Categorization of Portuguese Airports - operational indicators (2010)

Category	**Airport**	**Number of passengers**	**Number of direct routes**	**Number of airlines**	**Number of Airplane Movements**	**Volume of Freight Transport (tons)**	**Volume of Mail Transport (tons)**
Category A (>10 million passengers/ year)	Lisbon	14066545	100	28	138147	93870,6	11432,9
Category B (between 5 and 10 million passengers/ year)	Faro	5342707	61	23	39629	289	0
	Oporto	5279531	61	14	55432	35274,8	385,6
Category C (between 1 and 5 million passengers/ year)	Santa Cruz (Madeira)	2239353	55	37	25898	6286,1	2368,3
Category D (<1 million passengers/ year)	Ponta Delgada (S. Miguel)	935207	29	8	13115	5994,7	1486,8
	Lajes (Terceira)	477721	2	9	9788	2187,421	1140,095
	Horta (Faial)	190135	2	5	4734	800,2	279,6
	Porto Santo	105628	6	5	5032	213,6	108,7
	Santa Maria	87006	2	2	3362	2265,9	71,4
	Pico	60133	1	3	1370	221	150
	São Jorge	48541	1	2	1198	145	106
	Flores	42493	1	3	1500	172,4	68,1
	Graciosa	39670	1	2	1038	160	50
	Corvo	4491	1	3	526	37	17

Source: ANA (2010); ANAM (2010); SATA (2010); SREA (2010), own elaboration.

The three existing continental airports carry the most passengers on the list. Beside this, 11 of the Portuguese airports are located on the islands, where they rely heavily on

[1] Full text is available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:C:2005:312:0001:0014:EN:PDF

tourism and are subject to a certain level of seasonality. Some of those airports only provide direct destinations to one or two bigger airports with other routes. This is the case for 7 of the Azores airports and the Porto Santo airport, located in the Madeira archipelago. Even though those regional airports may not be profitable because of their scale, they also develop functions that are socially relevant (Vaz *et al.*, 2012), most notably:

- Providing a public service of extreme importance to those places where medical care is not available and which require urgent transport to bigger cities;
- Increasing mobility of local populations;
- Assisting the competitive edge and expansion of local markets.

To better understand the context of each airport, we collected data concerning the surrounding area of the airport.

The biggest airports have also a bigger area of influence, since they serve a bigger district or island, depending on the airport location. Lodging capacity (number of beds) and number of guests help to understand the power of attraction that each hinterland exercises over tourism and airport utilization (number of passengers carried by each airport). Table 5 resumes the collected variables.

Table 5 – Hinterland Information of Portuguese Airports (2010 or else if stated)

Airport	Area (km^2)	Population	Lodging Capacity	Number of Guests	Classified Heritage (2005)	Gross Added Value (2009)
Oporto	2395	1771622	19855	1509698	429	13156373
Lisbon	2761	2248925	49733	3621859	626	36266005
Faro	5412	437643	98980	2874136	205	2331197
Porto Santo	42,5	4387	2071	54096	6	15429
Santa Cruz (Madeira)	740,7	243181	26795	922263	37	1869726
Ponta Delgada (S. Miguel)	746,8	137741	5277	216148	82	827267
Santa Maria	97,2	5555	366	9545	12	10886
Horta (Faial)	173,1	14996	955	40947	51	45183
Flores	141,7	3806	339	6778	17	11508
Pico	447,7	14168	458	17911	30	29888
Corvo	17,1	429	14	508	4	648
Graciosa	61,2	4400	203	5748	15	7396
São Jorge	245,8	9192	185	6919	16	19282
Lajes (Terceira)	402,2	56445	1461	57598	75	193534

Source: INE (2010), SREA (2010), IGESPAR (2005), own elaboration.

Faro Airport neither carries freight nor mail, aside luggage from passengers. The number of Low-Cost (LC) passengers at Faro Airport has been growing on a yearly basis, whereas for the Porto Airport, which has a prevalent freight transport function, the LC carriers operate as a complement.

8. AN ANP MODEL FOR HINTERLAND VARIABLE SELECTION

8.1 Airports and hinterland indicators

Plenty of indicators have been used in the airport benchmarking process, including, most notably, operational indicators used both as inputs or outputs. Martens and van der Zwan (2011) completed a survey of 32 studies demonstrating which operational indicators were the most used (see Table 6):

Table 6– Most used indicators in airport studies

Indicator/Times used in the 32 studies			
Total number of passengers	ALL	Airport area	7
Number of airplane movements	25	Number of luggage reclaim belts/reclaim hall area	5
Invested capital/cost of capital	14	Total runway length	5
Total number of employees	13	Total cost	5
Total sales	13	Runway area	4
Number of runways	12	Number of car parking spots	4
Total labour cost	12	Number of check-in desks	4
Terminal Area	12	Apron area	3
Operational Cost	9	Number of aircraft parking stands	3
Aviation/non-aviation revenues	8	Profitability	2
Number of gates	8	Departure Lounge area	1

Source: Martens and van der Zwan (2011)

We specify another two indicators we consider critical for the assessment of the operational efficiency of airports:

- The number of direct routes present at each airport, which is critical to determine the degree of accessibility of the airport;
- The number of airlines operating at a given airport, which is directly correlated with the number of routes available.

Beyond those operational indicators, Postorino (2010) characterized the main indicators for the Catchment Area: population, households' disposable income, employment, sectorial structure of employment, population age structure, distance to other airports, and existent low-cost offer.

In their seminal work on the ‘geographical efficiency’ of Spanish regional airports, Tapiador *et al.* (2008) included the following indicators in their analysis: population, European resident population, a leisure-related services activity index, an economic activity index, a commercial activity index, an industrial activity index, a tourist activity index, the length of railway (km), the length of roads (km) and an estimate of inter-modality (the length of motorways/dual carriageways, railways and roads).

Our study aimed to include an initial set of 18 indicators, during the 2008-2010 yearly periods (2005 for Listed Heritage), for each Portuguese airport, and for each district or island they serve, when applicable:

Table 7 – Initial set of indicators for this study

1. Number of direct routes	2. Total number of guests
3. Number of airlines operating in each airport	4. Area (km^2)
5. Number of passengers	6. Listed heritage
7. Number of Airplane Movements	8. Gross Added Value of firms (10^3€)
9. Volume of Freight Transport (tons)	10. Exports (10^3€)
11. Volume of Mail Transport (tons)	12. Number of firms
13. Volume of Airport investments (10^3€)	14. Imports (10^3€)
15. Resident population	16. Loaded goods at the closest Ports
17. Total lodging capacity	18. Unloaded goods at the closest Ports

Most of the indicators were collected through the annual statistical publications of the National Institute of Statistics (INE) and its regional partners, annual accounting reports of SATA, and annual reports of ANA. Data for the listed heritage was collected at the National Institute of Heritage Management (IGESPAR). This study is limited by the following premises:

- Most of the variables, notably indexes, constructed by Tapiador *et al.* (2008) required data not available for Portugal, at the time of this study;
- The Regional Government of the Azores Islands did not release any statistical information about the airport under their management (Aerogare Civil das Lajes) at the time of this study;
- The districts of Lisbon and Oporto do not match the area of the metropolitan area, neither the NUTS III nomenclature. Data at the municipality level is hard or impossible to obtain, and has to be summed with all the municipalities that belong to these districts in order to obtain the district value;
- The calculation of an inter-modality index for means of transport, despite its vital importance for a balanced economic growth, had to be put aside, due to major differences between Islands and continental Portugal.

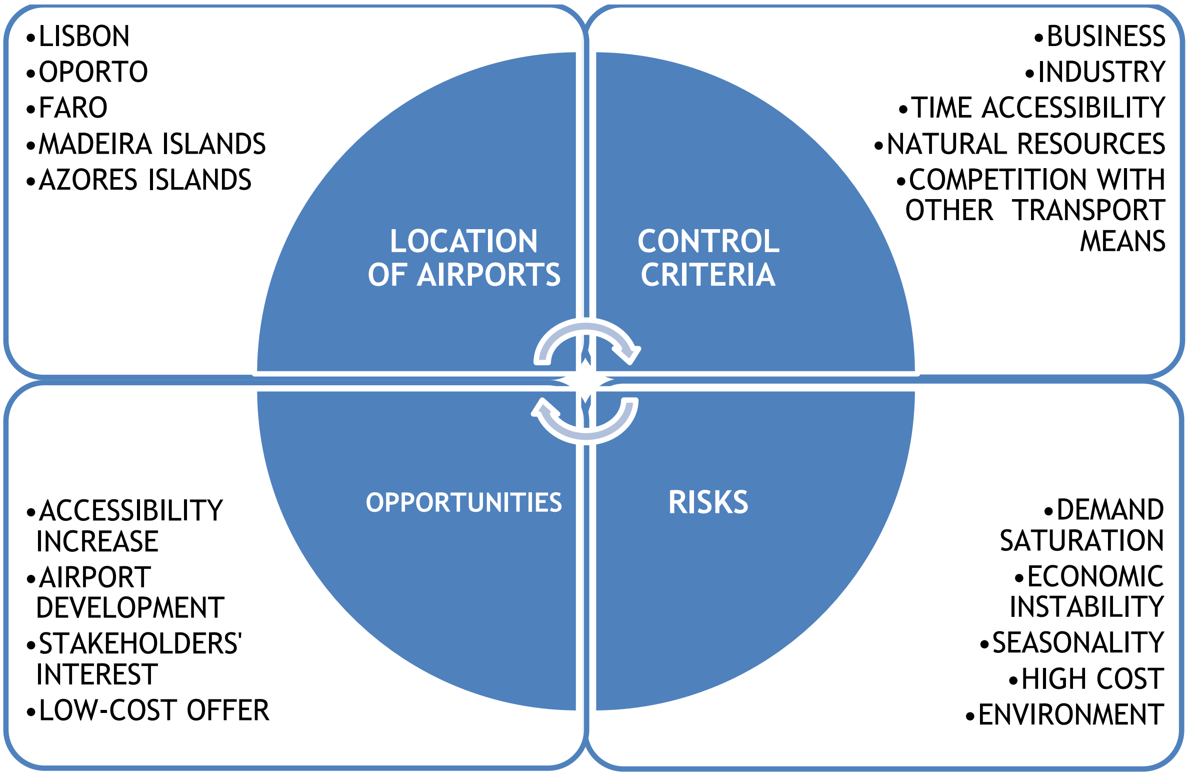
8.2 The ANP model and the selected variables

The assessment of the most important operational variables of airports to be included in an efficiency measurement is an issue that Ulutas and Ulutas (2009), with their ANP-DEA hybrid approach, tried to overcome.

The adoption of the ANP in our study is justified with the need to select the best indicators among a given set, based on a given number of criteria, and to overcome the “convergence” problem with DEA models referenced before, in order to build a model with a 3:1 level of proportionality between DMUs (Airports) and variables (Inputs and Outputs).

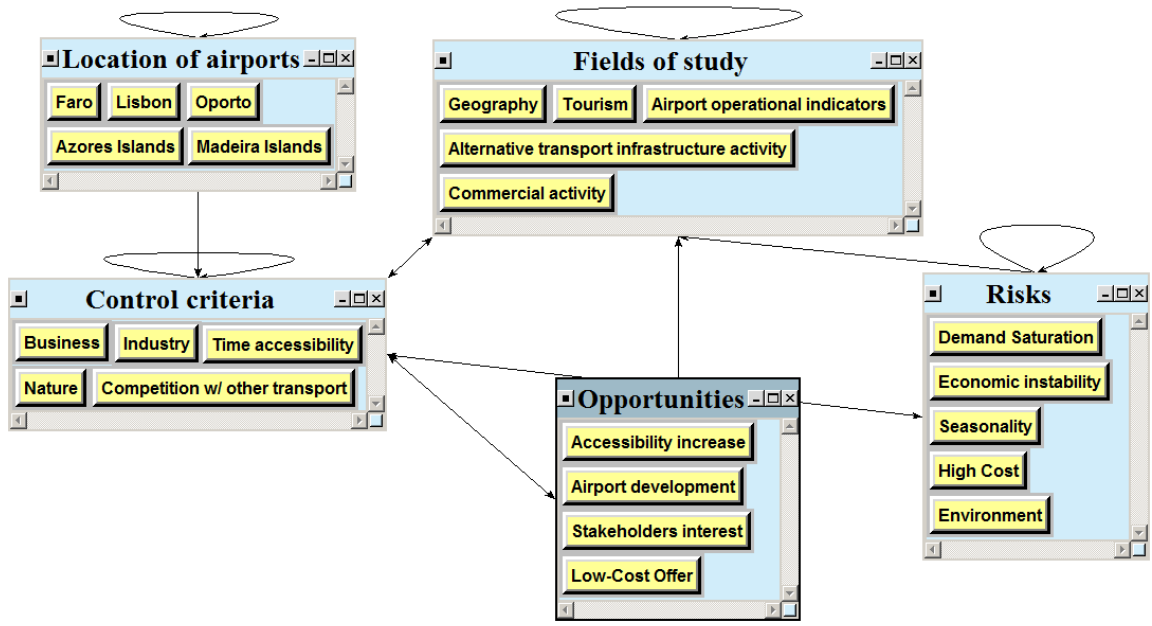
The next figure (Figure 4) depicts the selected dimensions: clusters in blue and nodes listed next, which require to be ranked according to their appropriateness for the problem under study. Favourable concerns are called opportunities while unfavourable ones are called risks.

Figure 4 – Hinterland Categorization Model



Source: own elaboration

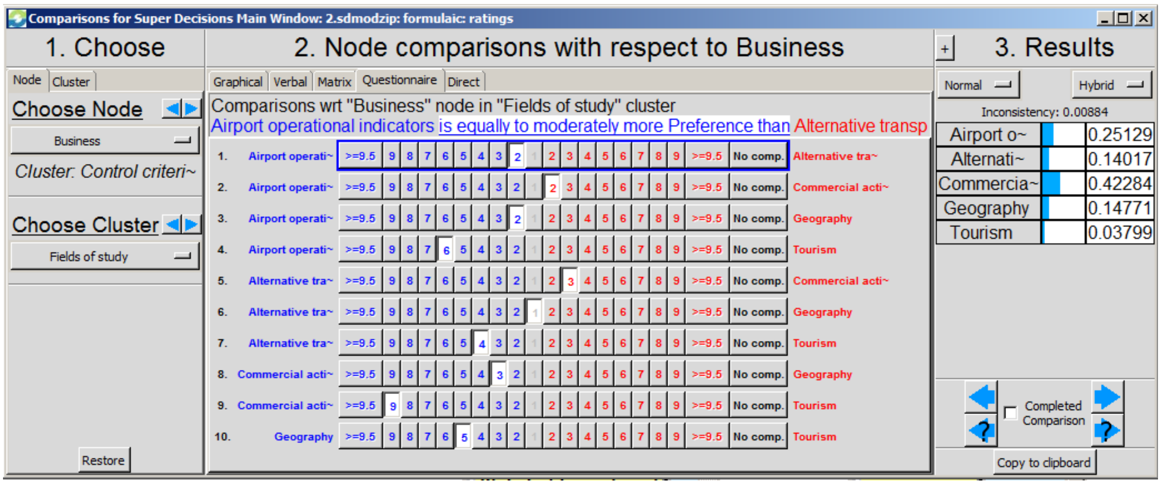
Figure 5 – Our ANP model for variable selection



Source: Super Decisions Software; own elaboration.

We use the ‘Location of Airports’ as the main driver to identify which of the variables are the most important. The ‘Control Criteria’ is the second most important factor, followed by the ‘Opportunities’ and ‘Risks’. Those categories are used as clusters in our ANP model to replicate the model depicted in the Figure 4, whereas the criteria are used as nodes. Thus the Figure 4 resumes the elements of our ANP model, and Figure 5 shows the final model as it is shown in the Super Decisions Software.

Figure 6 – Example of pairwise comparisons in our model



Source: Super Decisions Software; own elaboration.

Figure 6 indicates a sample of pairwise comparisons made in the Super Decisions Software. All the pairwise comparisons, or derived priorities, are resumed the unweighted supermatrix (Table 13, p.33). In the ANP component blocks of the supermatrix are multiplied by constants so that the columns will sum to 1, resulting in the weighted supermatrix (Table 14, p.33). Another matrix called limit supermatrix (Table 15, p.34) contains the final results, the priorities for the alternatives, as well as the overall priorities for all the other elements in the model, including the cluster matrix. The cluster matrix represents the derived priorities from comparisons between clusters (Table 16, p.34).

We use the 'ratings' function present in the Super Decisions software to classify variables according to criteria present in our ANP model. We rank them from 1 as 'preferable' to 17 as 'non preferable'. Rank 1 gets 17 points and rank 17 gets 1 point.

Table 8 features the results of the ANP model, including the selected variables to enter the DEA model. Variables are separated as 'output' when they are related to the operation of an airport, and 'input' when they are related to the hinterland.

Table 8 – Synthesis of the ANP model and selected variables

Name of the Variable (Year of availability when applicable)	**Type of Variable**	**Priority Ranking**	**Enters the DEA Model?**	**Nomenclature**
Number of Passengers (2010)	Output	1,00	**Yes**	Output 1
Number of Direct Destinations (2010)	Output	0,98	**Yes**	Output 2
Freight Transport (2010)	Output	0,85	**Yes**	Output 3
Number of airplane movements (2010)	Output	0,84	No	-
Population (2010)	Input	0,83	**Yes**	Input 1
Number of Airlines (2010)	Output	0,82	No	-
Geographical Area	Input	0,81	**Yes**	Input 2
Mail Transport (2010)	Output	0,71	No	-
Number of Guests (2010)	Input	0,69	**Yes**	Input 3
Gross Added Value (2009)	Input	0,64	**Yes**	Input 4
Lodging Capacity (2010)	Input	0,63	No	-
Exports (2010)	Input	0,61	No	-
Firms (2009)	Input	0,56	No	-
Imports (2010)	Input	0,52	No	-
Loaded Goods at Airports (2010)	Input	0,49	No	-
Listed Heritage Venues (2005)	Input	0,47	No	-
Unloaded Goods at Airports (2010)	Input	0,42	No	-

Source: Super Decisions, own elaboration

We adopt the 3:1 rule of thumb for the selection of variables according to the number of DMUs under study to avoid convergence. As we study fourteen DMUs, variables (inputs and outputs) will be four (3 inputs + 1 output) to enter the DEA model. We do DEA with each of the outputs selected, resulting in 3 different DEA, which results are different as if one DEA model with 3 outputs + 3 inputs was done (that model would not respect the proportionality and would give most of the DMUs on the efficient frontier).

The correlation matrix of the selected inputs is depicted in table 9. The correlation matrix is usually used to explore the linkage between variables. This correlation matrix was made with the econometrics software GRETL.

Table 9 – Correlation matrix of the selected inputs for DEA

	Population	Area	Number of Guests	Gross Added Value
Population	1.0000	0.5763	0.8139	0.9379
Area		1.0000	0.8798	0.4663
Number of Guests			1.0000	0.8037
Gross Added Value				1.0000

Source: own elaboration

We can see an overall very high correlation between the selected inputs, with exception to the population-area and area-gross added value correlations.

9. EMPIRICAL DEA MODEL AND AVERAGE SCORE TABLE

As stated in Chapter 5, the DEA model to be used in this study is a VRS input-oriented model. The software DEAP version 2.1 is used to obtain the DEA estimations (Coelli, 1996). Table 10 presents the ANP's selection of inputs and outputs to be used in the DEA estimations.

Table 10 – Outputs and Inputs for DEA

Airport	DMU	Out 1 - Pax	Out 2 - Dest	Out 3 - Cargo	Input 1 - Pop	Input 2 - Area	Input 3 - Guests	Input 4 - G.A.V.
Oporto	1	5279531	61	35274,8	1771622	2395	1509698	13156373
Lisbon	2	14066545	100	93870,6	2248925	2761	3621859	36266005
Faro	3	5342707	61	289	437643	5412	2874136	2331197
Porto Santo	4	105628	6	213,6	4387	42,5	54096	15429
Santa Cruz (Madeira)	5	2239353	55	6286,1	243181	740,7	922263	1869726
Ponta Delgada (S. Miguel)	6	935207	29	5994,7	137741	746,8	216148	827267
Santa Maria	7	87006	2	2265,9	5555	97,2	9545	10886
Horta (Faial)	8	190135	2	800,2	14996	173,1	40947	45183
Flores	9	42493	1	172,4	3806	141,7	6778	11508
Pico	10	60133	1	221	14168	447,7	17911	29888
Corvo	11	4491	1	37	429	17,1	508	648
Graciosa	12	39670	1	160	4400	61,2	5748	7396
São Jorge	13	48541	1	145	9192	245,8	6919	19282
Lajes (Terceira)	14	477721	2	2187,42	56445	402,2	57598	193534

Source: own elaboration

Results of the VRS DEA statistics are compiled in table 11. The value of the output 'Direct Destinations' had to be multiplied by ten for the VRS DEA model to generate results, due to limitations of the DEAP software; that exponentiation has no implications on the obtained efficiencies whatsoever (Coelli, 1996).

Table 11 – VRS DEA results for each output selected

		Technical Efficiency (CRS)			**Productive Efficiency (VRS)**			**Scale Efficiency**			**Returns to Scale**		
	DMU	**Pax**	**Dest**	**Cargo**	**Pax**	**Dest**	**Cargo**	**Pax**	**Dest**	**Cargo**	**Pax**	**Dest**	**Cargo**
Oporto	1	0,876	0,614	0,701	0,891	0,622	0,794	0,984	0.986	0,883	DRS	IRS	DRS
Lisbon	2	1	1	1	1	1	1	1	1	1	-	-	-
Faro	3	1	0,029	0,020	1	0,073	0,073	1	0,392	0,277	-	DRS	DRS
Porto Santo	4	1	0,211	0,217	1	1	1	1	0,211	0,217	-	IRS	IRS
Santa Cruz	5	1	0,614	1	1	1	1	1	0,614	1	-	IRS	-
Ponta Delgada	6	0,649	0,827	1	0,719	0,842	1	0,903	0,982	1	DRS	IRS	-
Santa Maria	7	1	1	1	1	1	1	1	1	1	-	-	-
Horta	8	1	0,748	0,851	1	1	1	1	0,748	0,851	-	IRS	IRS
Flores	9	0,882	0,162	0,164	1	1	1	0,882	0,162	0,164	IRS	IRS	IRS
Pico	10	0,663	1	0,425	1	1	0,671	0,663	1	0,634	IRS	-	DRS
Corvo	11	0,814	1	1	1	1	1	0,814	1	1	IRS	-	-
Graciosa	12	0,736	1	1	1	1	1	0,736	1	1	IRS	-	-
São Jorge	13	0,546	0,762	0,417	1	1	0,526	0,546	0,762	0,793	IRS	IRS	DRS
Lajes	14	1	0,966	0,966	1	0,981	0,973	1	0.984	0,992	-	IRS	IRS

Source: own elaboration

CRS or technical efficiency is meant as the 'distance' from a DMU from the best-in class performer, whereas VRS or productive efficiency is meant as the 'distance' from a DMU from the best-in class performer taking returns to scale into account. The scale efficiency is, as referred in equation (3), the ratio between CRS and VRS efficiency.

We can see that there are two CRS-efficient airports among the DMUs for every DEA made (Pax, Dest and Cargo outputs): Lisbon and Santa Maria. Lisbon is the main hub for Portuguese airlines, including the major company TAP, while Santa Maria is one of the regional airports of the Azores Islands controlled by ANA, with, by comparison, approximately 1% of the passenger traffic of Lisbon airport.

The results of the output 1 (**number of air passengers**) show that the majority of regional airports located in islands are operating below the optimum geographical scale efficiency, except Ponta Delgada, which operates at decreasing returns to scale. This means that, according to best-in class performers, these regional airports could take more profit from the selected inputs.

The results of the output 2 (**number of direct destinations**) show a lower CRS efficiency of DMUs 3 (Faro, DRS), 4 (Porto Santo, IRS) and 9 (Flores, IRS). Faro is a very particular case, where charters and LCC have a significant proportion of the routes available, while retaining a very high number of domestic passengers at Faro in traditional flights, and having a large concentration of passengers demand in a limited number of routes available (e.g. the UK airports), despite having plenty of routes. As the VRS efficiency improves very little over CRS efficiency, results of decreasing returns to scale can be explained by the way this airport is operating by comparison to the other airports of this sample, but are still surprising. Porto Santo and Flores (Flores has only one direct route available) are cases of regional airports relying heavily on other airports to transport passengers to their final destinations – Santa Cruz and Ponta Delgada, respectively. We see that these airports are fully VRS efficiency with output 2, meaning they are subject to increasing returns to scale, leaving room for improvement in both the direct routes available at each airport by comparison with other small regional airports present in our sample.

Relatively to output 3 (**Cargo**), one of the predictable results is the inferior CRS efficiency of DMU 3, which corresponds to Faro Airport, where almost no cargo is handled, but, once again, VRS efficiency improves only very slightly, resulting in decreasing returns to scale. Other very low CRS efficiencies obtained include DMU 4 (Porto Santo, explained by the presence of Madeira airport), DMU 9 (Flores), DMU 10 (Pico) and DMU 13 (São Jorge). We can see that VRS efficiencies improve well over CRS efficiencies in DMUs 4 (Porto Santo) and 9 (Flores), resulting in increasing returns to scale, whether we see decreasing returns to scale in DMUs 10 (Pico) and 13 (São Jorge). We have, then, very mixed results in Islands regarding the efficiency of the cargo volume output towards the hinterland inputs. On the other hand, DMU 1 (Oporto Airport) is operating at decreasing returns to scale (even though we expect these to be relatively minor).

These results provide results which should be combined to give an overall balance of how an airport operates effectively according to its hinterland. We think that the sole passenger dimension is unable to capture at least the necessary ties between airport and hinterland. Thus, in order to fully address the geographical efficiency of airports, we propose another measure of efficiency called 'Average Score', for which we will do DEA estimations with each of the three priority outputs selected for the final model. To obtain a synthesis of the overall efficiency of the selected airports regardless of their scale of operations, the priorities of the ANP model are used to weight the technical efficiencies obtained in the DEA models and create an average score outside the DEA parameterizations, according to the following equation, which is used to obtain table 12:

$$eDMU_i = \frac{\sum_{j=1}^{3} eDMU_{ij} \times Priority_j}{\sum_{j=1}^{3} Priority_j}$$

Where:

$$eDMU_i = Average\ Score\ of\ each\ DMU$$

$$eDMU_{ij} = Technical\ Efficiency\ of\ DMUs\ with\ each\ Output\ j$$

$$Priority_j = Output\ Priorities$$

$$i = 1, \dots, 14;\ j = 1,2,3$$

Table 12 – Final average score of the Portuguese Airports

Lisbon	1	Ponta Delgada (S. Miguel)	0,816064
Santa Maria	1	Oporto	0,73271
Lajes (Terceira)	0,978014	Pico	0,708216
Corvo	0,934276	São Jorge	0,582053
Graciosa	0,906714	Porto Santo	0,491601
Horta (Faial)	0,867982	Flores	0,417018
Santa Cruz (Madeira)	0,866332	Faro	0,369406

Source: own elaboration

Given the results of table 12, we can see that, considering the geographical area, some airports are clearly oversized in regard to their hinterland, as it is the case with the airports of Flores, Porto Santo and São Jorge, with Flores being the most relevant case. Faro airport occupies the last place in the final average score, notably due to the great number of direct routes available and the policy of ANA to route cargo transport to Oporto and Lisbon. Interestingly enough, we see that Corvo airport, the smallest airport on our list, occupies the fourth place. This is probably due to the regional strategy of SATA Airlines, jointly with SATA aerodromes, to use certain airports which are geographically strategic for the definition of the inter-island flights. The airports of Santa Maria (first place, shared with Lisbon) and Lajes (third place), with only two direct routes each, do a remarkably good job to enhance the hinterland capabilities, albeit not functioning fully as transfer sites for lesser used airports. Oporto obtains a slightly lower ranking by comparison to Lisbon. This seems to point to a great unused economic potential present in the area and the fact that Oporto is essentially used by LCC, giving the airport a high number of direct routes. Furthermore, Oporto and Faro have a much greater Catchment Area than the district, which is a limitation of our study.

Interestingly enough, the two major island airports, Santa Cruz (Madeira) and Ponta Delgada (S. Miguel), have a fairly similar average score, with a minor advantage to Madeira. Even though Madeira has a more evidenced tourism and, consequently, a greater utilization of the airport, the two airports manage to take mostly the same advantages in proportion to their hinterland inputs.

10. DISCUSSION OF EMPIRICAL RESULTS

The ANP model allowed a better understanding of the premises that stand behind the selection of a variable. We saw that airports have different operational efficiencies according to their hinterland inputs, which answers positively to the first main question of this study.

The CRS efficiencies showed mixed results for the following categories of airports, turning impossible any efficiency separation between:

- General operations vs. Low-Cost operations;
- Continent vs. Island;

- International vs. Regional.

Thus, our first question “Is the operational efficiency of airports affected by the distinctive features of their hinterland?” remains unclear, as it is difficult to express all the differences between different geographical areas with only 4 hinterland indicators.

Our ANP-DEA model was not totally able to capture the benefits of low-cost operations in airports due to the limited area covered – if we consider that low-cost airports allow a greater catchment area – and the difference in the demand of direct routes among airports. Hence, an answer to our second question “To what extent the resources and characteristics of the hinterland contribute to operational efficiency of airports?” remains also uncertain.

Nevertheless, of the continental airports, Lisbon maintains the leadership as the most efficient airport in every quadrant of analysis. We found that Faro airport is operating poorly for outputs 2 and 3 according to the hinterland variables, and at decreasing returns to scale. Oporto airport, which is said to be one of the best airports according to operational indicators, obtains a relatively low level of overall CRS efficiency, which is patent in the final average score. Oporto has a better technical efficiency score in terms of the cargo volume over Faro.

In the islands, Santa Maria obtains a surprising first place tied with Lisbon, for which we see a good contribution of the local resources to the expected outputs of the airport, meaning that this airport is both operating efficiently and at an optimal scale.

11. FINAL CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

This study explored Portuguese airports’ geographical efficiency with interesting results, which are obviously limited by the low number of Portuguese airports and the availability of data. We see that the location and the surrounding area of airports plays a determinant role for a good operation of the airport in terms of passengers, whilst the number of routes available sees decreasing returns to scale for the airports with the most routes (with Lisbon being the main exception). Cargo operations depend effectively on the proportionality between what is carried and the area served by these operations. There are some limitations related to the following aspects:

- The size of the sample is rather low;
- Only 4 hinterland inputs have been designated;
- The geographical size of every airport is not taken into account when considering inputs and outputs.

Nevertheless, a new landmark is set for the study of the geographical efficiency of Portuguese airports, extending on the geographical efficiency work of Tapiador *et al.* (2008) by doing a prioritization of the variables. A set of more correlated variables can be, thus, interesting to be compared with the ones available for this study. For example, the 'Number of Direct Routes' output we use in this study is subject to be complemented in the future with a ratio of seasonality, albeit depending on the appropriateness of available data. A question remains unanswered with this work: to what extent the resources and characteristics of the hinterland do contribute to the operational efficiency of airports?

- The extension of the study to the whole Iberian Peninsula can take our efforts further, since the inclusion of a greater number of DMUs allows the inclusion of more variables;
- The availability of a greater period of data would allow doing a Malmquist-TFP productivity change over time, which is interesting to evaluate, for example, how much regional investments could have effectively contributed to improve the general efficiency of airports.

Another application of regional benchmarking is taking the inverse path we follow in this study: the application of regional efficiency ranking of regions based on the airports' and other factors contribution. That kind of study would contribute to add input-output analysis to the literature of regional impacts studies. We believe that this ANP-DEA model can be seen as an alternative to OLS regressions and catalytic methods in regional studies, where they are currently preferred.

BIBLIOGRAPHY

ACI (2006). Airport Benchmarking to Maximize Efficiency. ACI World Headquarters, Geneve.

ADAMAKI-TZAVELLA, E.; PISTELLI, L.; HAAG, G.; HREHUSOVA, A.; VOUGIOUKAS, M. (2008). Regional airports interaction for regional and tourism development. Leisure and Tourism Transport Seminar, European Transport Conference Proceedings 2008.

BANKER, R.; CHARNES R.; COOPER, W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science Journal, Vol. 30, pp. 1078-1092.

BARROS, C.; DIEKE, P. (2007). Performance evaluation of Italian airports: A Data Envelopment Analysis. Air Transport Management, 13, pp. 184-191.

BARROS, C.; DIEKE, P. (2008). Measuring the Economic Efficiency of Airports: A Simar-Wilson Methodology Analysis. Transportation Research Part E: Logistics and Transportation, 44,6, 1039-1051

BELLONI, J. (2000). Uma Metodologia de avaliação da eficiência produtiva de Universidades Federais Brasileiras. Tese de Doutoramento, Universidade Federal de Santa Catarina. Florianápolis.

Brueckner, J. (2003). Airline Traffic and Urban Economic Development. Urban Studies, 40, 1455-1469.

CASA NOVA, S.; SANTOS, A. (2008). Application of the Data Envelopment Analysis using Accounting Variables. Revista de Contabilidade e Organizações, Vol. 2, pp. 132-153.

CHARNES, A.; COOPER, W.; RHODES E. (1978). Measuring the Efficiecy in Decision Making Units. European Journal of Operational Research, Vol. 2, Issue 6, pp. 429-444.

CHEN, H.; WOOD, M.; MALBY, L. (2011). Uncertainty analysis in a GIS-based multicriteria analysis tool for river catchment management. Environmental Modeling & Software Journal, Vol. 26 (4), pp. 395-405.

COELLI, T. (1996). A Guide to DEAP Versio 2.1: A Data Envelopment Analysis (Computer) Program. Centre for Efficiency and Productivity Analysis, Department of Econometrics, University of New England, Australia.

COOPER, W. W.; SEIFORD, L. M.; ZHU, J. (2003). Data Envelopment Analysis: History, Models and Interpretations. Handbook of Data Envelopment Analysis, Chapter 1.

EIB (1998). Contribution of Major Road and Rail Infrastructure Projects to Regional Development. Luxembourg.

FARRELL, M. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Vol. 120, pp. 253-288.

FERREIRA, L.; STEVENS, N.; BAKER, D. (2006). The New Airport and its Urban Region: Evaluating Transport Linkages. In Proceedings International Conference of Transport and Traffic Studies.

FRANCIS, G.; HUMPHREYS, I.; FRY, J. (2002). The Benchmarking of Airport Performance. Journal of Air Transport Management, Vol. 8, no. 4, pp. 239-247.

GRAHAM, A. (2005). Airport Benchmarking: A Review of the Current Situation. International Journal, Vol. 12 (2), pp. 99-111.

HÁJEK, O.; GREBENÍCEK, P. (2010). Regional airports in the Czech Republic: focused on geographical efficiency.

HASAN, M; SHANKAR, R; SARKIS, J. (2008). Supplier selection in an agile manufacturing environment using data envelopment analysis and analytical network process. International Journal of Logistics, Inderscience.

HENSHER, D.; WATERS, W. (1994). Light Rail and Bus Priority Systems: Choice or Blind Commitment? 3rd International Conference on Competition and Ownership of Land Passenger Transport, Canada.

HIRSCHAUSEN, C.; CULLMANN, A. (2005). Questions to Airport Benchmarkers: Some Theoretical and Pratical Aspects Learned from Benchmarking Other Sectors. German Aviation Research Society Conference on Airport Benchmarking, Viena.

IZQUIERDO, R. (1997). Gestión y Financiación de las Infraestruturas del Transporte Terrestre. Asociación Española de la Carretera, Madrid.

BRAZ, J.; BALTAZAR, E.; JARDIM, J.; SILVA, J.; VAZ, M. (2012). Performance and Efficiency Evaluation of Airports. The Balance Between Data Envelopment Analysis (DEA) and Multi Criteria Decision Analysis (MCDA) Tools, AIRDEV Proceedings 2012, pp. 11-29.

KINCAID, I.; TRETHEWAY, M. (2009). Methodology Choices for Benchmarking Aeroports.

LEMAITRE, A. (1998). The Development of Performance Indicators at Airports: A Management Perspective. 8th World Conference on Transport Research, Antwerp.

LIEBERT, V.; NIEMER, H. (2010). Benchmarking of Airports: A Critical Assessment.

MALINA, R. (2008). Using a Contingent Valuation Approach for Evaluating the Benefits of Airports for Regional Economies. 7th Conference on Apllied Infrastructure research; Berlin.

Martens, R; ZWAN, F. (2011). Benchmarking Airport Efficiency: Regional Airport Terminal Processes. Delft University of Technology, Netherlands, November of 2011.

MÜLLER, J.; MÜLLER, C.; EHMER, H.; NIEMER, H. (2009). Market Entry and Market Exit in European Airport Market.

NEUFVILLE, X; GUZMÁN, X; (1998). Benchmarking for Design of Major Airports Worldwide. J. Transp. Eng. 124(4), pp. 391-395.

PAVLYUK, Dmitri (2012). Airport Benchmarking and Spatial Competition: A Critical Review. In Transport and Telecommunication Journal, Vol. 13, No. 2, pp. 123–137.

RAMANATHAN, R. (2006). Data envelopment analysis for weight derivation and aggregation in the analytic hierarchy process. Computers & Operations Research Journal, Vol. 33, Issue 5, pp. 1289–1307.

GREEN, R. (2007). "Airports and Economic Development," Real Estate Economics, American Real Estate and Urban Economics Association, vol. 35 (1), pp. 91-112, 03.

RIETVELD, P. (1989). A Survey of Multiregional Economic Models. Annals of Regional Science: Infrastructure and Regional Development, Vol. 23, No. 4.

ROYENDEGH, B. D.; EROL, S. (2009). A DEA-ANP Hybrid Algorithm Approach to Evaluate an University's Performance. International Journal of Basic and Applied Sciences, Vol. 9, pp. 115-129.

SAATY, T. (1977). A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology, Vol. 15, pp. 234–281.

SAATY, T. (1980). The Analytic Hierarchy Process. Mc-Graw Hill: New York.

SAATY, T. (1996). Decision Making with Dependence and Feedback: The Analytic Network Process. RWS Publications: Pittsburgh.

SAATY, T. (2001). The Analytic Network Process: Decision Making with Dependence and Feedback. RWS Publications: Pittsburgh.

SARKIS, J. (1999). A methodological framework for evaluating environmentally conscious manufacturing programs. Computers & Industrial Engineering 36 (1999), pp. 793-810.

SCHAAR, D.; SHERRY, L. (2008). Comparison of Data Envelopment Analysis Methods Used in Airport Benchmarking. 3rd International Conference on Research in Air Transportation, ICRAT 2008. Fairfax, VA.

SEIFORD, L. (1997). A Bibliography for Data Envelopment Analysis (1978-1996). Annals of Operations Research, No. 73, pp. 393-438.

STEWART, J 2009 Heathrow campaigners - heading for a historic victory? International Journal of Green Economics. Nr. 3, pp.462-468

STIMSON, R. J.; STOUGH, R. R.; ROBERTS, B. H. (2006). Regional Economic Development: Analysis and Planning Strategy. Springer: 2nd edition.

TAPIADOR, F. J.; MATEOS, A.; MARTÍ-HENNEBERG, J. (2008). The Geographical Efficiency of Spain's Regional Airports: A Quantitative Analysis. Journal of Air Transport Management, no. 14, pp. 205–212.

TAVARES, G. (2002). A Bibliography for Data Envelopment Analysis (1978-2001). Rutcor Research Report. New Jersey: Rutgers University.

THÜNEN, V. (1826). Der Isolierte Staat. Paderborn, Germany, 2011 Reprint.

TRB, 2007 ACRP PROGRAM SYNTHESIS 7: Airport Economic Impact: Methods and Models. WASHINGTON, D.C.

TSAI, W. H.; KUO, H. C. (2011). A hybrid approach for multi-criteria evaluation of airport service quality. In the International Journal of Services and Standards. Inderscience Publisher.

ULUTAS, B.; ULUTAS, B. (2009). An Analytic Network Process Combined Data Envelopment: Analysis Methodology to Evaluate the Performance of Airports in Turkey. Eskisehir Osmangazi University, Department of Industrial Engineering, Turkey.

VAZ, M.; SILVA, J.; BALTAZAR, E.; MARQUES, T. (2012). Regional Airports, Tourism And Development: Two Portuguese Case Studies. 2nd Advances in Hospitality and Tourism Marketing & Management Conference (AHTMMC), Corfu, Greece, Conference Proceedings.

VREEKER, R.; NIJKAMP, P.; TER WELLE, C. (2001). A Multicriteria Decision Support Methodology for Methodology for Evaluating Airport Expansion Plans. Tinbergen Institute Discussion Paper, p.21

WEISBROD, G.; REED, J.; NEUWITH, R.; (1993). Airport Area Economic Development Model. PTRC International Transport Conference, Manchester, England.

YILMAZ, A. K. (2008). Importance of the Enterprise Risk Management Practice for Airline Management: ANP-based Approach. International Journal of Business and Management, Vol. 3, No. 5.

12. ATTACHMENTS

Table 13 - Unweighted Super Matrix

		Business	Competiti	Industry	Nature	Time acce	Airport op	Alternativ	Commerci	Geograph	Tourism	Azores Isl	Faro	Lisbon	Madeira Is	Oporto	Accessibil	Airport de	Low-Cost	Stakehold	Demand S	Economic	Environm	High Cost	Seasonalit
Control cr	Business	0	0	0	0	0	0,112475	0,097781	0,309112	0,049413	0,065806	0,077376	0,165396	0,341482	0,148863	0,101782	0	0	0	0	0	0	0	0	0
	Competiti	0	0	0	0	0	0,416405	0,379806	0,067416	0,224843	0,189492	0,033296	0,118679	0,074661	0,040754	0,109743	0	0	0	0	0	0	0	0	0
	Industry	0	0	0	0	0	0,048218	0,127376	0,474062	0,100699	0,036247	0,224995	0,031264	0,090405	0,072234	0,438971	0	0	0	0	0	0	0	0	0
	Nature	0	0	0	0	0	0,051772	0,034552	0,03881	0,42007	0,426277	0,413472	0,35388	0,181092	0,463918	0,109743	0	0	0	0	0	0	0	0	0
	Time acce	0	0	1	0	0	0,37113	0,360486	0,1106	0,204975	0,282178	0,25086	0,330782	0,31236	0,274231	0,239762	1	0	0	0	1	0	0	0	0
Fields of s	Airport op	0,251289	0,128207	0,193483	0,073338	0,352348	0	0	0	0	0	0	0	0	0	0	0,047619	0	0	0	0,092149	0	0	0	0
	Alternativ	0,140174	0,438333	0,177717	0,081491	0,037077	0	0	0	0	0	0	0	0	0	0	0,428571	0	0	0	0,038893	0	0	0	0
	Commerci	0,42284	0,036284	0,475212	0,079419	0,111232	0	0	0	0	0	0	0	0	0	0	0,047619	0	0	0	0,267427	0	0	0	0
	Geograph	0,147711	0,355796	0,097586	0,183121	0,374507	0	0	0	0	0	0	0	0	0	0	0,428572	0	0	0	0,154108	0	0	0	0
	Tourism	0,037986	0,041381	0,056002	0,582631	0,124835	0	0	1	0	0	0	0	0	0	0	0,047619	0	0	0	0,447423	0	0	0	0
Location c	Azores Isl	0	0	0	0	0	0	0	0	0	0	0	0,079969	0,14796	0,070948	0,079756	0	0	0	0	0	0	0	0	0
	Faro	0	0	0	0	0	0	0	0	0	0	0,25	0	0,419279	0,201049	0,226006	0	0	0	0	0	0	0	0	0
	Lisbon	0	0	0	0	0	0	0	0	0	0	0,25	0,596635	0	0,529331	0,595041	0	0	0	0	0	0	0	0	0
	Madeira Is	0	0	0	0	0	0	0	0	0	0	0,25	0,099463	0,018441	0	0,099197	0	0	0	0	0	0	0	0	0
	Oporto	0	0	0	0	0	0	0	0	0	0	0,25	0,223932	0,414321	0,198672	0	0	0	0	0	0	0	0	0	0
Opportun	Accessibil	0,25	0,25	0,25	0,25	0,25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Airport de	0,25	0,25	0,25	0,25	0,25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Low-Cost	0,25	0,25	0,25	0,25	0,25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Stakehold	0,25	0,25	0,25	0,25	0,25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Risks	Demand S	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Economic	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,222222	0	0	0	0
	Environm	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,444444	0	0	0	0
	High Cost	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,333333	0	0	0	0
	Seasonalit	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Source: Super Decisions Software

Table 1413 – Weighted Super Matrix

		Control criteria						Fields of study						Location of airports						Opportunities					Risks
		Business	Competiti	Industry	Nature	Time acce	Airport op	Alternativ	Commerci	Geograph	Tourism	Azores Isl	Faro	Lisbon	Madeira Is	Oporto	Accessibil	Airport de	Low-Cost	Stakehold	Demand S	Economic	Environm	High Cost	Seasonalit
Control cr	Business	0	0	0	0	0	0,112475	0,097781	0,154556	0,049413	0,065806	0,025792	0,055132	0,113827	0,049621	0,033927	0	0	0	0	0	0	0	0	0
	Competiti	0	0	0	0	0	0,416405	0,379806	0,033708	0,224843	0,189492	0,011099	0,03956	0,024887	0,013585	0,036581	0	0	0	0	0	0	0	0	0
	Industry	0	0	0	0	0	0,048218	0,127376	0,237031	0,100699	0,036247	0,074998	0,010421	0,030135	0,024078	0,146324	0	0	0	0	0	0	0	0	0
	Nature	0	0	0	0	0	0,051772	0,034552	0,019405	0,42007	0,426277	0,137824	0,11796	0,060364	0,154639	0,036581	0	0	0	0	0	0	0	0	0
	Time acce	0	0	0,25	0	0	0,37113	0,360486	0,0553	0,204975	0,282178	0,08362	0,110261	0,10412	0,09141	0,079921	0,666667	0	0	0	0,692308	0	0	0	0
Fields of s	Airport op	0,083763	0,042736	0,048371	0,024446	0,117449	0	0	0	0	0	0	0	0	0	0	0,015873	0	0	0	0,021265	0	0	0	0
	Alternativ	0,046725	0,146111	0,044429	0,027164	0,012359	0	0	0	0	0	0	0	0	0	0	0,142857	0	0	0	0,008975	0	0	0	0
	Commerci	0,140947	0,012095	0,118803	0,026473	0,037077	0	0	0	0	0	0	0	0	0	0	0,015873	0	0	0	0,061714	0	0	0	0
	Geograph	0,049237	0,118599	0,024396	0,06104	0,124836	0	0	0	0	0	0	0	0	0	0	0,142857	0	0	0	0,035563	0	0	0	0
	Tourism	0,012662	0,013794	0,014	0,19421	0,041612	0	0	0,5	0	0	0	0	0	0	0	0,015873	0	0	0	0,103251	0	0	0	0
Location c	Azores Isl	0	0	0	0	0	0	0	0	0	0	0	0,053313	0,09864	0,047299	0,053171	0	0	0	0	0	0	0	0	0
	Faro	0	0	0	0	0	0	0	0	0	0	0,166667	0	0,279519	0,134033	0,150671	0	0	0	0	0	0	0	0	0
	Lisbon	0	0	0	0	0	0	0	0	0	0	0,166667	0,397757	0	0,352887	0,396694	0	0	0	0	0	0	0	0	0
	Madeira Is	0	0	0	0	0	0	0	0	0	0	0,166667	0,066309	0,012294	0	0,066131	0	0	0	0	0	0	0	0	0
	Oporto	0	0	0	0	0	0	0	0	0	0	0,166667	0,149288	0,276214	0,132448	0	0	0	0	0	0	0	0	0	0
Opportun	Accessibil	0,083333	0,083333	0,0625	0,083333	0,083333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Airport de	0,083333	0,083333	0,0625	0,083333	0,083333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Low-Cost	0,083333	0,083333	0,0625	0,083333	0,083333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Stakehold	0,083333	0,083333	0,0625	0,083333	0,083333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Risks	Demand S	0,066667	0,066667	0,05	0,066667	0,066667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Economic	0,066667	0,066667	0,05	0,066667	0,066667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,017094	0	0	0	0
	Environm	0,066667	0,066667	0,05	0,066667	0,066667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,034188	0	0	0	0
	High Cost	0,066667	0,066667	0,05	0,066667	0,066667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,025641	0	0	0	0
	Seasonalit	0,066667	0,066667	0,05	0,066667	0,066667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Source: Super Decisions Software

Table 15 – Limit Matrix

		Control criteria					Fields of study						Location of airports						Opportunities					Risks
		Business	Competiti	Industry	Nature	Time acce	Airport op	Alternativ	Commerci	Geograph	Tourism	Azores Isl	Faro	Lisbon	Madeira Is	Oporto	Accessibil	Airport de	Low-Cost	Stakehold	Demand S	Economic	Environm	High Cost	Seasonalit
ontrol cr	Business	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0,028165	0	0	0	0,028165	0	0	0	0
	Competiti	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0,083005	0	0	0	0,083005	0	0	0	0
	Industry	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0,031149	0	0	0	0,031149	0	0	0	0
	Nature	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0,080376	0	0	0	0,080376	0	0	0	0
	Time acce	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0,174811	0	0	0	0,174811	0	0	0	0
ields of s	Airport op	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0,043977	0	0	0	0,043977	0	0	0	0
	Alternativ	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0,036402	0	0	0	0,036402	0	0	0	0
	Commerci	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0,028358	0	0	0	0,028358	0	0	0	0
	Geograph	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0,06513	0	0	0	0,06513	0	0	0	0
	Tourism	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0,060885	0	0	0	0,060885	0	0	0	0
ocation c	Azores Isl	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Faro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Lisbon	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Madeira Is	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Oporto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
pportun	Accessibil	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0	0	0	0,045478	0	0	0	0
	Airport de	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0	0	0	0,045478	0	0	0	0
	Low-Cost	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0	0	0	0,045478	0	0	0	0
	Stakehold	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0,045478	0	0	0	0,045478	0	0	0	0
isks	Demand S	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0	0	0	0,036382	0	0	0	0
	Economic	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0,037253	0	0	0	0,037253	0	0	0	0
	Environm	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0,038124	0	0	0	0,038124	0	0	0	0
	High Cost	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0,037689	0	0	0	0,037689	0	0	0	0
	Seasonalit	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0,036382	0	0	0	0,036382	0	0	0	0

Source: Super Decisions Software

Table 16 – Cluster Matrix

	Control cr	Fields of s	Location c	Opportun	Risks
Control cr	0,25	0,5	0,333333	0,666667	0,692308
Fields of s	0,25	0,5	0	0,333333	0,230769
Location c	0	0	0,666667	0	0
Opportun	0,25	0	0	0	0
Risks	0,25	0	0	0	0,076923

Source: Super Decisions Software