Combining the priority rankings of DEA and AHP methodologies: a case study on an ICT industry

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Abstract: This article presents a case study on how data envelopment analysis (DEA) and analytic hierarchy process (AHP) could be combined to produce priority rankings for a set of companies. The shortcomings of each method, when exclusively used to deal with multiple criteria decision analysis (MCDA) problems, are also analysed. The dataset of this study, arising from the European Union (EU) *Industrial R&D Investment Scoreboard* (European Commission, 2009), consists of the top EU companies activating in the telecommunications equipment industry, which is one of the most representative information and communications technology (ICT) industries. Five criteria, namely, R&D investment, number of employees, capital expenditure, net sales, and operating profit, are used for defining priority rankings of these companies. The application of the case study indicates that the super-efficiency DEA model could be employed for ranking the companies at an initial stage; following that, ranking of the efficient companies could be attained through AHP.

Keywords: multi-criteria analysis; decision making; data envelopment analysis; DEA; analytic hierarchy process; AHP.

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1 Introduction

Multiple criteria decision analysis (MCDA) constitutes a scientific field that aims to support decision making through numerous and conflicting evaluations (Roy, 1996; Vincke, 1992). MCDA can be efficiently utilised in order to handle both qualitative and quantitative criteria. A lot of methodologies have been developed for the solution of MCDA problems (Koutroumanidis et al., 2002; Manos et al., 2007; Manos et al., 2010). Some of them include analytic hierarchy process (AHP), data envelopment analysis (DEA), goal programming (GP) and others. The main difference between all these decision methodologies is the way that the objectives and the weights of criteria and alternatives are computed.

This article presents a comparison between AHP and DEA. The purpose of the article is to exhibit the similarities and differences of the two methods in dealing with the same MCDA problem. DEA is a non-parametric approach that can be used to measure the performance of a number of decision making units (DMUs). In our case, a DMU is a company belonging to the ICT industry. According to the literature, a problem tackled by DEA is one which may equally well be approached using multiple criteria analysis (Belton and Vickers, 1993).

On the other hand, AHP uses pairwise comparisons to determine ratio-scale weights to prioritise the criteria and the alternatives in an intuitively elegant manner, developed by Saaty (2007). A major benefit of the AHP methodology is that, a decision making problem is analysed in sub-problems hierarchised using different criteria. Thus, even large and complex problems with controversial criteria can be significantly simplified. It is noteworthy that INFORMS awarded the 2008 Impact Prize to Professor Thomas Saaty for his seminal work on the AHP. AHP is now an established methodology that is part of the operational research (OR) curriculum for multi-criteria decision-making in business and engineering schools, and described in a lot of books (Forman and Selly, 2001).

Furthermore, software for its implementation is readily available, e.g., Expert Choice (2010) Version 11.5.

2 DEA as a MCDA tool

DEA is a non-parametric technique, which has been widely used to measure the relative efficiency of a number of DMUs that utilise a set of inputs to produce a set of outputs (Charnes et al., 1978). Its aim is to identify the efficient DMUs, the DMUs which are not efficient and to assess where the inefficiencies arise. Moreover, it provides the possibility to rank the DMUs in terms of their efficiency, i.e., the ability to convert multiple inputs into multiple outputs. DEA avoids problems due to incorrect specifications, since it is not based in any assumptions on the functional form between inputs and outputs, as for example, with the parametric econometric approach of stochastic frontier analysis (SFA).

The optimisation problem which DEA solves is stated as follows: maximise the efficiency score of the unit under evaluation subject to the constraints that the efficiency scores of all the units are lower than or equal to unity. Since the variables in a DEA model are the weights of inputs and outputs, the model finds the optimum weights in order to maximise the efficiency of the unit under evaluation. Four basic DEA models are generally distinguished (Cooper et al., 2007):

- *Charnes, Cooper, and Rhodes (CCR) model:* it is based on the radial minimisation (maximisation) of all inputs (outputs) by assuming constant returns to scale (CRS), i.e., a proportional increase in all inputs results in a proportional increase of the output (Coelli et al., 2005).
- *Banker, Charnes, and Cooper (BCC) model:* it assumes variable returns to scale (VRS), i.e., a proportional increase in all inputs results in an increase of the output, but not at the same proportion. The difference with the previous model is that, the BCC model adds a convexity constraint to the constraints of the linear programming problem.
- *Additive model:* While the CCR and BCC models are either input-oriented or output-oriented, the additive model combines both orientations in a single approach. It deals with the input excesses and output shortfalls simultaneously and is independent on the coordinate system of the dataset.
- *Slacks-based measure (SBM) model:* It provides a scalar measure of efficiency which encompasses all the inefficiencies that the additive model can identify. It is invariant with respect to the unit of measurement of each input and output item, but not invariant to the coordinates of the dataset.

The basic DEA models do not always provide good discriminating characteristics among DMUs, especially in situations where a significant number of DMUs are efficient. Besides, in basic DEA models the number of efficient units may be relatively high, hindering in that way the rank ordering of DMUs. This is a problem that could be dealt with by the super-efficiency DEA model (Andersen and Petersen, 1993; Mehrabian et al., 1999), where the efficient units get scores greater than one. These scores can be used for classification purposes of the efficient units. However, using super-efficiency measures, an infeasible solution to some of the linear programming problems of the DEA model is always possible, when convexity constraints are to be dealt with (VRS). Using the

SBM model, Tone (2002) introduced non-radial super-efficiency models to eliminate deficiencies with regard to infeasible solutions.

Stewart (1996) has compared the goals of DEA and MCDA. As already said, DEA models deal with situations where the goal is to determine the productive efficiency of a number of DMUs by comparing how well these units convert inputs into outputs. In MCDA models there are a number of alternatives (options) between which the decision maker has to decide and each alternative is described by its performance on each of a number of criteria, attributes or objectives. A criterion is defined as a particular point of view according to which alternatives can be assessed and rank-ordered; an attribute is a particular feature of the alternative with which a numerical measure can be associated; an objective is a specific direction of preference defined in terms of an attribute. According to Steward, MCDA and DEA formulations coincide, if we view inputs and outputs as attributes or criteria for evaluating DMUs, with minimisation of inputs and/or maximisation of outputs as associated objectives. This point is in line with the methodological approach of Doyle and Green (1993) and Li and Reeves (1999), who applied DEA as a multiple criteria decision making (MCDM) model. Moreover, Sarkis (2000) claims that DEA seems to perform well as a discrete alternative MCDM tool. The findings of his study show that additional constraints in DEA models, which incorporate decision maker value judgments, can provide comparable results between DEA and traditional MCDM approaches. Generally, these constraints are associated with the variation (upper and lower bounds) allowed for input and output weights (Madlener et al., 2009). Liu et al. (2009) propose a multiple criteria DEA/assurance region (AR) model, which can solve cost-type, fixed-type and income-type criteria simultaneously. They also utilise AHP method to reflect the decision maker's preferences. This hybrid model takes account both objective and subjective views.

The aforementioned references indicate that DEA can be used as a discrete alternative MCDA tool. It is true that, there is not a generally accepted approach for making comparisons between DEA and well established MCDA tools. This implies that the investigation of the relationship of the two methodologies needs further consideration. Nevertheless, its indisputable advantages make DEA a useful tool to deal with MCDA problems, especially when little information is provided to decision makers.

3 The AHP methodology

The AHP methodology constructs hierarchies with a number of levels according to the number of criteria and sub-criteria. Usually, the first level corresponds to the initial decision, the next levels correspond to the problem criteria, and the following levels are expanded according to the specific sub-criteria until we reach the terminal criteria. AHP is based on judgments on pairs of elements and uses eigenvector and eigenvalue theory in order to prioritise the criteria and the alternatives.

The main advantages of AHP over other multiple criteria methods are its convenience, flexibility and the ability to check inconsistencies. As already mentioned in Section 1, a decision problem is decomposed through AHP into its constituent parts, enabling the decision maker to comprehend the importance of each criterion, and each alternative as well. In uncertain and risky situations where quantitative data are restricted, the judgments of experts for defining the weights of the criteria and the scores of the alternatives could be proved very useful.

AHP method is widely used for several years and have a lot of benefits but also certain drawbacks. AHP is widely used in a significant number of research areas, including selection and ranking problems, and business analytics to mention but a few. Although a plethora of AHP applications have been reported in the literature, e.g., in healthcare management (Vidal et al., 2010), project management (Al-Harbi, 2001), fisheries management (Leung et al., 1998), AHP has been mainly criticised as not adhering to rank reversal situations. A rank reversal situation is likely to occur when an irrelevant alternative is added to the set of existing alternatives. However, several researchers (Forman, 1993; Triantaphyllou, 2001) claim that the rank reversal problem (Pérez et al., 2006) can be addressed without causing a change in the ranks of the existing alternatives. Furthermore, among the drawbacks of the method, one could mention that the application of AHP is usually a lengthy task due to the large number of pairwise comparisons of the alternatives $\frac{mn(n-1)}{2}$ (where m, n is the number of criteria and alternatives, respectively).

In order to eliminate the limitations of both DEA and AHP methodologies, new integrated models DEA-AHP have been reported in the literature (Jyoti et al., 2008; Wang et al., 2008; Yang and Kuo, 2003). The majority of those hybrid models uses the optimal weights as derived by DEA in order to determine the pairwise comparisons needed in AHP. Innovative applications of AHP have recently emerged, using approaches from mathematical programming, artificial intelligence, and geographical information systems (Ho, 2008; Triantafyllidis et al., 2007; Temiz and Tecim, 2009).

4 Case study

4.1 The dataset

The dataset used in this research derives from the European Union (EU) *Industrial R&D Investment Scoreboard*, published by the Institute for Prospective Technological Studies of the Joint Research Centre (JRC/IPTS) on behalf of the European Commission (2009). All the data have been drawn from the latest available companies' accounts, i.e., the fiscal year 2008. The full dataset of the 2009 EU *Industrial R&D Investment Scoreboard* is available in the JRC/IPTS website (European Commission, 2009). The scoreboard provides data concerning the R&D ranking of the top 1,000 EU companies, as well as the top 1,000 non-EU companies. The term 'EU company' (or 'non-EU company') refers to companies whose ultimate parent has its registered office in a member state of the EU (or outside the EU). The scoreboard document is in a spreadsheet format, presenting the R&D investments of these companies in many different industries; however, our research is only focused on the EU companies activating in the telecommunications equipment industry. This industry is one of the most significant ICT-related industries, with a high growth rate in R&D investment. This is despite the consequences of the economic crisis which started in the second half of 2008. An interesting point is that, out of 37 industrial sectors, the top three in R&D investment, accounting for more than 53% of the total investment, are:

1 pharmaceuticals and biotechnology
2 technology hardware and equipment (including telecommunications equipment)
3 automobiles and parts.

The selection of the telecommunications equipment is also due to the fact that it is a typical ICT industry; hence, a survey of this industry would provide a representative view of the whole set of ICT-related industries.

For the purposes of ranking the sampled companies, five criteria have been used:

1 number of employees
2 capital expenditure
3 R&D investment
4 net sales
5 operating profit.

Table 1 Data of the DMUs

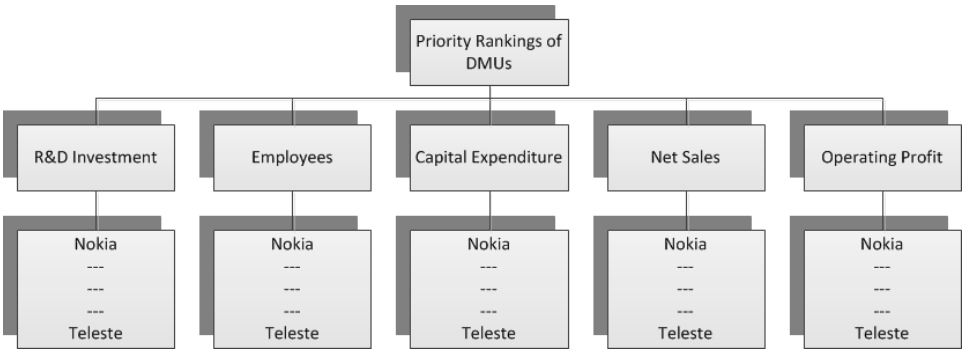
DMU	*R&D investment*	*Employees*	*Capital expenditure*	*Net sales*	*Operating profit*
Nokia	5,321.00	121,723	1,073.00	50,710.00	4,972.00
Alcatel-Lucent	3,167.00	77,717	414.00	16,984.00	–5,200.00
Ericsson	2,975.46	78,989	376.02	19,008.17	1,368.50
Italtel	93.93	2,319	9.47	467.79	–29.43
GN Store Nord	71.35	4,786	17.87	755.64	4.57
Pace	61.63	762	6.81	771.12	15.00
Spirent Communications	46.86	1,547	7.66	266.77	50.69
ADVA	40.96	1,031	4.10	217.67	–7.04
Option	37.04	656	2.83	268.09	–29.30
Wavecom	33.56	420	0.00	202.34	12.64
Parrot	26.99	470	2.37	206.58	15.58
Thrane & Thrane	20.55	693	1.73	165.99	16.48
Sepura	15.83	306	1.82	76.65	10.87
Tecnomen	15.45	358	1.05	77.21	11.54
Radiall	12.72	2,486	15.17	200.37	16.66
Amper	11.11	1,270	3.80	359.06	27.40
Vislink	9.41	543	2.43	104.50	0.89
Telit Communications	8.78	339	1.73	60.37	–2.27
Filtronic	7.00	610	2.39	87.33	–26.31
Ubiquisys	6.80	41	0.62	0.03	–10.62
Net Insight	6.39	101	1.15	24.96	3.45
CEAG	6.00	18,488	6.62	315.22	12.37
Amino Technologies	5.13	119	0.24	33.00	1.35
Apertio	5.13	193	0.43	20.45	–3.88
Newport Networks	4.88	70	0.27	0.14	–10.09
Trafficmaster	4.50	585	1.62	57.69	5.86
Teleste	4.42	702	0.58	108.70	3.93

The first three are minimising criteria (cost-input), while the latter two maximising ones (benefit-output). A brief description of these criteria follows:

- *Number of employees:* it is the average number of employees or the respective number at the end of the year, if average not stated. This criterion is associated with the most important resource of a company, i.e., labour.
- *Capital expenditure:* it is the expenditure used by a company to acquire or upgrade physical assets, such as equipment, buildings, etc.
- *R&D investment:* it is the cash investment funded by the companies themselves. It excludes joint venture R&D investment and R&D undertaken under contract for customers, such as governments.
- *Net sales:* it is calculated as the amount of sales, excluding sales taxes, after the deduction of returns, allowances for damaged or missing goods and any discounts allowed.
- *Operating profit:* it is calculated as the profit of the company before deduction of interest payments and income taxes.

Figure 1 depicts the AHP hierarchy of the dataset belonging to the proposed case study.

Figure 1 AHP hierarchy of the dataset



4.2 Research methodology

Our research is based on an integrated DEA-AHP model. DEA has not only been used to evaluate the performance of a set of entities in terms of their ability to convert inputs into outputs. It has also been widely used to provide new insights into issues and activities that have been evaluated by other methodologies, as for instance MCDA (see Section 2). Such an issue is ranking a set of companies with respect to a number of minimising and maximising criteria. However, ranking is not an easy task since a high number of efficient units (units with an efficiency score equal to one) usually arise in basic DEA models. This is the reason why we decided to use the super-efficiency DEA model, which is analytically described in Cooper et al. (2007). According to this model, the efficient unit under evaluation is excluded from the reference set, resulting in the construction of a new efficient frontier and the calculation of a higher than unity efficiency score. It is a fact that the use of the various super-efficiency models has been restricted to situations

where CRS are assumed, due to possible infeasible solutions of the linear programming problems in the case of another type of returns to scale. In our case, CRS is a valid assumption since a proportional increase in all the input items would most probably result in an increase of the output at the same proportion (doubling, for instance, the number of employees, the amount of R&D investment and the amount of capital expenditure would lead to the double amount of sales or profit, like having two identical companies). Therefore, we applied to this empirical study the super-efficiency I-C model (input orientation, CRS); all the computations were carried out with the DEA-Solver software (SAITECH Inc., 2010).

Although, the ranking results of the inefficient companies are unquestionable and the ranking process could be finished by using only the super-efficiency model, the ranking of the efficient units requires much more attention. Several researchers (e.g., Banker and Chang, 2006) have demonstrated that the use of a super-efficiency model for ranking efficient DMUs is inappropriate. Moreover, there are certain conditions in the CRS super-efficiency model which can lead to infeasibility, as for instance, the excluded DMU to be extreme efficient or to have the only zero value for any input (Lovell and Rouse, 2003). To avoid these problems, we selected to employ the AHP methodology for ranking the efficient companies, which have arisen from the application of the super-efficiency I-C model. So, the current study is one of the many approaches in literature that combine the strengths (and weaknesses) of a quantitative and a qualitative method. A difference on how we applied the AHP methodology compared to its usual applications is that we did not use the subjective evaluations of a panel of experts. Since the criteria are common business measures, such as the number of employees or the operating profit of a company, the order of the importance of the criteria was operating profit, net sales, R&D investment, number of employees, and capital expenditure, taking into consideration their relative significance generally in business. These criteria have more or less the same significance in the telecommunications equipment industry, as in any other industry. The pairwise evaluations of all the efficient companies with respect to each criterion were assigned by defining thresholds in the range of values of these companies. We also took into consideration whether the criterion under evaluation was a maximising (output for DEA) or a minimising one (input for DEA), specifying the order of preference, either from the maximum value to the minimum or the reverse. Expert Choice software was used for the application of the AHP methodology. By using this approach, a low overall inconsistency ratio equal to 0.02 was achieved (which cannot always be guaranteed using a heterogeneous expert panel).

4.3 Results

Table 2 depicts the efficiency scores and ranking of all the sampled companies according to the normal DEA model (CRS, input orientation). The efficient DMUs are eight out of 27, i.e., a percentage of about 30%. These are fully efficient DMUs, meaning that not only their efficiency score equals to unity, but they also have neither excesses in the three input items nor shortages in the two output items. Ranking of the companies of the dataset is not feasible due to the number of efficient DMUs.

Table 2 DEA CCR-I results (basic DEA input model)

Company	*Score*	*Rank*
Nokia	1	1
Alcatel-Lucent	0.370	24
Ericsson	0.589	15
Italtel	0.387	23
GN Store Nord	0.458	20
Pace	1	1
Spirent Communications	1	1
ADVA	0.414	21
Option	0.664	14
Wavecom	1	1
Parrot	0.957	10
Thrane & Thrane	0.919	11
Sepura	0.957	9
Tecnomen	1	1
Radiall	0.531	16
Amper	1	1
Vislink	0.521	18
Telit Communications	0.390	22
Filtronic	0.461	19
Ubiquisys	0.001	27
Net Insight	0.836	12
CEAG	1	1
Amino Technologies	0.673	13
Apertio	0.311	25
Newport Networks	0.003	26
Trafficmaster	0.528	17
Teleste	1	1

The results from the application of the super-efficiency model (CRS, input orientation) are listed in Table 3. If we exclude the efficient companies, which now get efficiency scores greater than unity, the results concerning the inefficient companies are almost identical to the results of the normal DEA model. Correlation between the datasets of the inefficiency scores of the two DEA models (normal and super-efficiency) is strongly significant at the 0.01 level (Pearson's $r = 0.982$, sig (two-tailed) value < 0.001). Consequently, the preference ratings of the inefficient companies using either the DEA CCR-I model or the DEA super efficiency I-C are almost identical. To avoid any minimal differences between the two models, we follow the ranking of the super-efficiency model.

Table 3 DEA super efficiency I-C results (input-constant returns to scale)

Company	*Score*	*Rank*
Nokia	1.139	5
Alcatel-Lucent	0.336	23
Ericsson	0.518	15
Italtel	0.345	22
GN Store Nord	0.445	18
Pace	1.664	2
Spirent Communications	1.038	7
ADVA	0.367	20
Option	0.606	13
Wavecom	1	8
Parrot	0.924	9
Thrane & Thrane	0.908	10
Sepura	0.903	11
Tecnomen	1.074	6
Radiall	0.331	24
Amper	1.739	1
Vislink	0.486	17
Telit Communications	0.345	21
Filtronic	0.426	19
Ubiquisys	0.001	27
Net Insight	0.674	12
CEAG	1.209	4
Amino Technologies	0.562	14
Apertio	0.281	25
Newport Networks	0.003	26
Trafficmaster	0.498	16
Teleste	1.280	3

According to the methodology of this study, the efficient companies were ranked using AHP. The results are given in Table 4. There are significant differences between DEA and AHP with regard to the ranking of the efficient companies. As shown in this table, Nokia has a much higher relative weight (0.245) than all the other companies. This is due to the large amount of profit and sales of Nokia compared to the respective values of the other companies; it is reminded that profit and sales had the first and second highest relative importance among the criteria evaluated. On the other hand, DEA ranks Nokia in the fifth position among the eight efficient companies since this company has also much larger input items. This is a distinct discrepancy between the two methodologies; in AHP the pairwise evaluations of the criteria have a crucial impact upon the ranking of the alternatives, while DEA identifies only minimising and maximising criteria without any predefined relative importance. Figure 2 depicts the relative efficiencies and weights of DEA and AHP, respectively.

Figure 2 DEA relative efficiencies and AHP relative weights

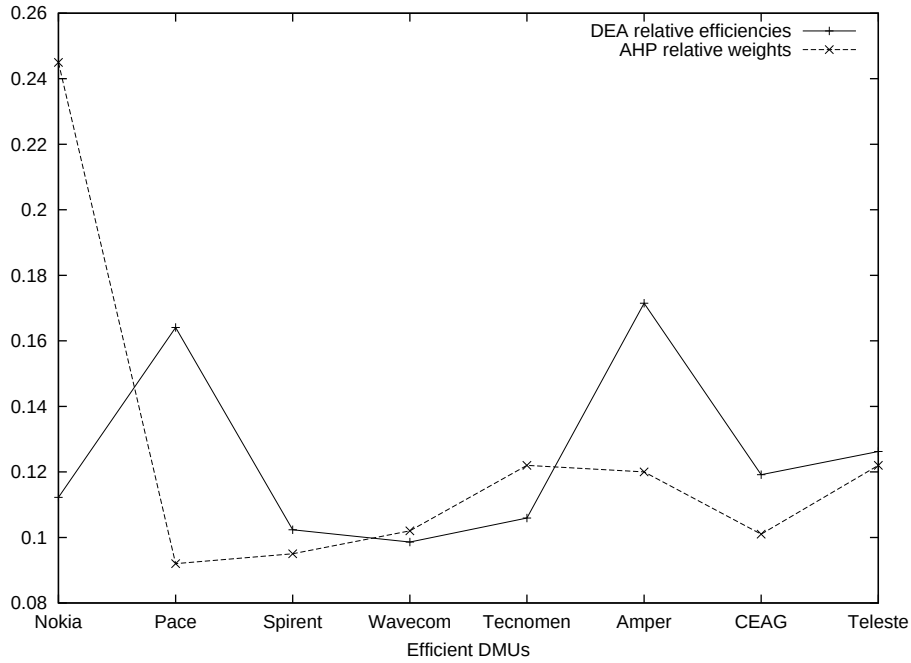


Table 4 AHP priority ranking of the efficient DMUs

Company	*Ranking*
Nokia	0.245
Tecnomen	0.122
Teleste	0.122
Amper	0.120
Wavecom	0.102
CEAG	0.101
Spirent Communications	0.095
Pace	0.092

5 Conclusions

In this paper, we presented a case study on how DEA and AHP methodologies could be combined in order to define priority rankings regarding a set of companies. Defining priority rankings is a very important task; as mentioned earlier, Eurostat publishes R&D ranking of companies which belong to several industries. However, this is not enough since R&D investment is a unique criterion. An institute, for example, which would be interested in sponsoring these companies, would like to have a list of priority rankings based on a number of criteria.

The dataset of this study consists of the top EU companies activating in the telecommunications equipment industry. Although we selected one of the most representative ICT industries, our primary target was neither to give an overall view of this business sector nor to provide a ranking of its companies. We explicitly focused on describing an integrated methodology for ranking companies based on a number of minimising and maximising criteria. Since DEA and AHP are methods which could be exclusively used for this purpose, we firstly analysed their weaknesses when each method is employed on its own. DEA can be used as a MCDA tool, but ranking among efficient units can be dealt only with the super-efficiency model; however, infeasibilities can arise using this DEA model. Even though we accept that infeasibilities cannot arise in an output-oriented CRS super-efficiency model, this is only a specific case in the numerous problems treated by DEA. On the other hand, AHP can be easily used only when the number of alternatives under evaluation is small. Another issue that AHP has been criticised for is the subjectivity of the pairwise evaluations. According to our methodological approach, we overcame this difficulty by defining thresholds in the range between the maximum and the minimum value of all the alternatives. Therefore, the use of either DEA or AHP on its own has certain disadvantages.

We demonstrated through the case study that the best possible priority rankings could be attained by combining the two methodologies. It is rather simple to rank the inefficient companies arising from the super-efficiency DEA model. But ranking the efficient companies is a task which has to be attended more thoroughly. Our suggestions are summarised in the following lines: if there is no information concerning the relative importance of the criteria used in the analysis, then ranking of the efficient companies should be accomplished using DEA. Otherwise, if the criteria are distinguished with respect to their relative importance, AHP should be used for ranking the efficient companies; we established that the pairwise evaluations of the criteria have a crucial impact on the final priority rankings resulting from AHP.

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