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Full Length Research Paper

Selecting the high - performing departments within universities applying the fuzzy MADM methods

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In this study, the process of efficiency measurement is tackled using multi-attribute decision-making (MADM) processes where a sequential algorithm is proposed. The framework of the study is based on two main stages; first, the data envelopment analysis (DEA), separately formulating each pair of units, formulates the department evaluation problem. DEA is a nonparametric multiple criteria method; no production, cost, or profit function is estimated from the data. In the second stage, the pair-wise evaluation matrix generated in the first stage is utilized to fully rank-scale the units via the fuzzy analytical hierarchical process (FAHP). The FAHP method adopted here uses triangular fuzzy numbers (TFN). Inability of AHP to deal with the impression and subjectiveness in the pair-wise comparison process has been improved in Fuzzy AHP. Instead of a crisp value, Fuzzy AHP a range of value to incorporate the decision maker's uncertainly.

Key words: Data envelopment analysis (DEA), fuzzy analytical hierarchy process (FAHP), triangular fuzzy numbers (TFN), multi criteria decision-making (MCDM), multi-attribute decision-making (MADM), fully-rank.

INTRODUCTION

Multi-attribute decision-making (MADM) is the most well known branch of decision-making. It is a branch of a general class of operations research models that deal with decision problems under the presence of a number of decision criteria. The MADM approach requires that the selection be made among decision alternatives described by their attributes. MADM problems are assumed to have a predetermined, limited number of decision alternatives. Solving a MADM problem involves sorting and ranking.

Decision-making is characterized as a process of choosing the best alternative(s) among a set of alternatives, in order to reach a goal (or goals). In the decision-making process, the most common representation format used by a decision-maker (DM) is a preference relation (or called pairwise comparison) since it is very useful in expressing his/her information about alternatives (Genc et al., 2010). The analytic hierarchy process (AHP), was proposed by Saaty (1980) and is one of the most popular method based on the preference relation in decision-making literature. The main advantage of AHP is to provide a systematic, validated approach for consolidating information about alternatives using multiple criteria (Kontio, 1996). The AHP has been applied to many different areas such as, project management (Al-Harbi, 2001) enterprise resource planning (ERP) system selection (Wei et al., 2005), risk assessment (Tsai and Su, 2005), knowledge management tools evaluation (Ngai and Chan, 2005).

The AHP is a well-known method for solving decision-making problems. AHP is one of the most widely used MADM methods. In this method, the DM performs pair-wise comparisons and, then, the pair-wise comparison matrix and the eigenvector are derived to specify the weights of each parameter in the problem. The weights guide the DM in choosing the superior alternative.

The other important method in decision-making literature is data envelopment analysis (DEA) measuring the relative efficiency of peer decision-making units (DMUs) with multiple inputs and multiple outputs was introduced by Charnes et al. (1978). This method is based on linear programming (LP), which gives it the ability to measure the decision units in a relative manner, though it has difficulties in measuring different scales and more than one scale, as well as in comparing entries or outputs that are in different units. MCDM is a modeling and methodological tool for dealing with complex engineering problem. However, the MCDM literature was entirely separate from DEA research until 1988, when Golany combined interacive, multiple-objective linear programming and DEA. Whilst the MCDM literature does not consider a complete ranking as their ultimate aim, they discuss the use of preference information to further refine the discrimiatory power of the DEA models. In this manner, the decision-makers could specify which inputs and outputs should lend greater importance to the model solution. However, this could also be considered the weakness of this method, since additional knowledge on the part of the decision-makers is required. Golany (1988), Kornbluth (1991), Golany and Roll (1994), Zhu (1996b) and Halme et al. (1999) each incorporated preferential information into the DEA models through, for example, a selection of preferred input/output targets or hypothetical DMUs. A separate set of papers reflected preferentrial information through limitations on the values of the weights, which can almost gurarantee a complete DMU ranking (Adler et al. 2002).

DEA has been applied to DMUs in various forms, such as hospitals, cities, universities, business firms and many others, for example, the handbook on DEA edited by Cooper et al. (2004). DEA, during the last decade, there have been attempts to fully-rank units in the context of DEA. Cook and Kress (1990), Cook et al. (1992) and Green et al. (1996) used subjective decision analysis. Norman and Stoker (1991) asserted a step-by-step approach that uses the selected simple ratios between input and output couples. Ganley and Cubbin (1992) improved the common weights, which maximizes the efficiency rates for all units. Sinuany-Stern et al. (2000) ordered all units by using linear discriminated analysis that is based on the given DEA dichotomic classification. Friedman and Sinuany-Stern (1997) used canonical correlation analysis (CCA/DEA) to order the units that are fundamental in common weights. Friedman and Sinuany-Stern (1998) developed the discriminate analysis of ratios instead of traditional linear discriminate analysis. Also (DR/DEA) Oral et al. (1991) used the cross-efficiency matrix for choosing R&D projects. There are deficiencies in all methods related to the nature of the methods themselves. Some of the deficiencies occur due to human faults, and some occur due to the presence of a large number of options.

Data envelopment analysis (DEA) a popular method has been extensively used for ranking and classiffying the decision making units. DEA, a nonparametric technique, is an alternative to multivariate statistical methods when it is used for the data with multiple inputs and outputs. DEA provide researchers a wide usage opportunity since it does not need any assumptions, unlike the multivariate statistical methods and it has a flexibility to add new restrictions to model according to researchers need.

MADM ranks elements based on single or multiple criteria, where each criterion contributes positively to the overall evaluations. The decision maker often carries out the evaluations subjectively. However, DEA deals with classifying the units into two categories, efficient and inefficient, based on two sets of multiple outputs contributing positively to the overall evaluation (Ganley and Cubbin, 1992 and Rouyendegh and Erol, 2010). The original DEA does not perform fully ranking, it merely provides classification into two dichotomic groups: efficient and inefficient. It does not rank them-all efficient units are equally good in the pareto sense. On the other hand, in AHP method, pair wise comparision is generally constructed by subjective preference of DMs. Therefore, in this paper, a hybrid model combining AHP and DEA is proposed to avoid the pitfalls of each method and applied to select the best department at a university.

LITERATURE REVIEW

The application of DEA to universities has generally focused on the efficiencies of university programs departments. The studies are by Bessent et al. (1983), Tomkines and Green (1988), Beasley (1990), Johnes and Johnes (1993), Stern et al.(1994), Johnes and Johnes (1995), Leitner et al. (2007) and Rayeni (2010).

Bessent et al. (1983) used DEA in measuring the relative efficiency of education programs in a community college. Educational programs (DMUs) were assessed on such outputs are revenue from state goverment. Number of students completing a program, and employer satisfacation with training of students. These outputs represented significant planning objectives. Inputs included student contact hours, number of full-time equivalent instructors, square feet of facilities for each program, and direct instructional expenditures. The authors demonstrated how DEA can be used in imporoving program, termnating programs, initiating new programs, or discountinuing inefficient program.

Tomkins and Green (1988) studied the overall efficiency of university accounting departments. They ran a series of six efficiency models of varying complexity where staff numbers was an input and student numbers an output. Results indicated that different configurations of multiple incommensurate inputs and outputs producted substantially stable efficioency score. On the other hand, beasley studied chemistry and physics departments on productive efficiency where financial variables such as research income and expenditure were treated as inputs. Outputs consisted of undergraduate and postgraduate student numbers as well as research rating. İn a follow-up study, Beasley analysed the same data set in an effort to determine the research and teaching efficiencies jointly,

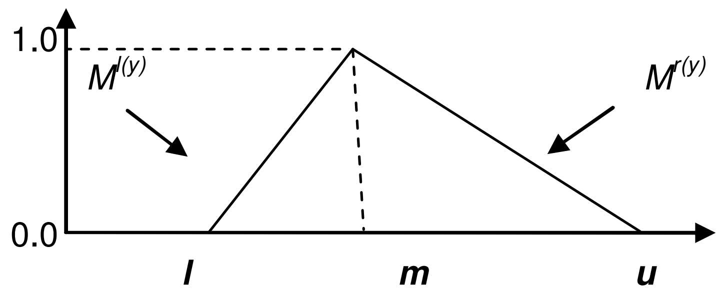

Figure 1. A triangular fuzzy number $\tilde{M}$

where weight restrictions were used.

Johens and Johnes (1995) explored various models in measuring the technical efficiency of economics department in terms of research outputs. They discuss the potential problems in choosing inputs and outputs. The authors also provide a good guide to interpreting efficiency scores. İt is interesting to note that both beasley(1990) and Johnes list research income as an inputs.

Stern et al.(1994) examined the relative efficiency of 21 academic department in Ben-Gurion University. Operating costs and salaries were entered as inputs, while grants, publications, graduate students, and contact hours comprised the outputs. Analysis suggested that the operating costs could be reduced in 10 departments. Furthermore, the authors tested for the sensitivity of efficiency score to deleting or combining variables. Their finding indicated that efficient departments may be re-rated as inefficient as a result of changing the variable mix. Similarly, Nunamaker, who has investigated the effects of changing the variable mix on DEA scores, reported a general rise when new variables were added or existing variables disaggregated.

Leitner et al. (2007) examined the measure efficiency in the university sector, as well as to apply DEA in the frame of Austrian university. DEA exceeds traditional methods analysing a universities' activities using simple ratio calculations. On the one hand, it determines the performance efficiency of university departments, on the other hand, it goes beyond this task and shows the improvement potential for each evaluated unit separately.

Rayeni (2010) explored the evolution of productivity of the university departments operating in the Islamic Azad University Zahedan Unit's education departments for the period 2004-2009. Since, the Islamic Azad University Zahedan Unit's education departments are part of the public sector where economic behavior is uncertain and there is no price information on the services produced, the Malmquist index based on DEA approach is well suited for productivity measurement where staff numbers(professors, assistant professor, lecture and educational expert), number of registered student in the term of the academic year, number of presented units in each department by gust lectures was an input and number of graduates in the academic year, number of student passing to higher level, Research (books, published article or presented in authentic conferences and report and reasearch projects) an output.

PRELIMINARIES

Fuzzy sets and fuzzy number

Zadeh (1965) introduced the fuzzy set theory to deal with the uncertainty due to imprecision and vagueness. A major contribution of this theory is its capability of representing vague data; it also allows mathematical operators and programming to be applied to the fuzzy domain. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function, which assigns to each object a grade of membership ranging between zero and one (Kahraman et al., 2003).

A tilde '~' will be placed above a symbol if the symbol represents a fuzzy set. A triangular fuzzy number (TFN), $\tilde{M}$ is shown in Figure 1. A TFN is denoted simply as ($l/m,m/u$) or (l,m,u). The parameters l, m and u $(l \le m \le u)$, respectively, denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event. The membership function of triangular fuzzy numbers is as follows:
Each TFN has linear representations on its left and right side, such that its membership function can be defined as

$$\mu\left(\frac{x}{\tilde{M}}\right) = \begin{cases} 0, & x < l, \\ (x-l)/(m-l), & l \le x \le m, \\ (u-x)/(u-m), & m \le x \le u, \\ 0, & x > u. \end{cases} \quad (1)$$

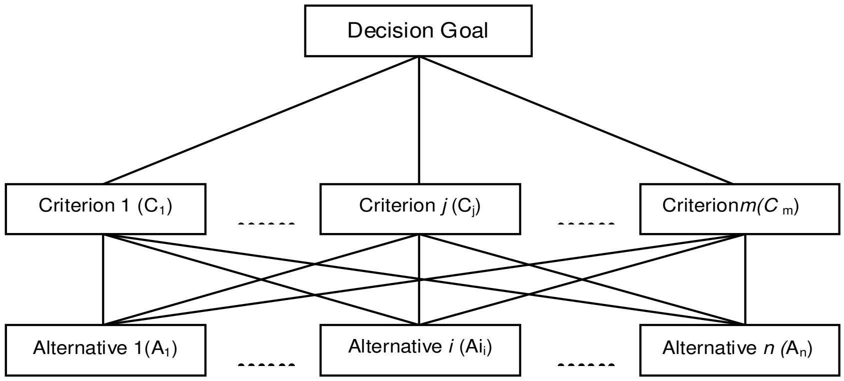

Figure 2. Hierarchy for a typical three-level MCDM problem (Wang et al., 2007).

Table 1. The 1-9 The fundamental scale of absolute numbers.

Importance intensity	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement slightly favor one over another
5	Strong importance of one over another	Experience and judgment strongly favor one over another
7	Very strong importance of one over another	Activity is strongly favored and its dominance is demonstrated in practice
9	Extreme importance of one over another	Importance of one over another affirmed on the highest possible order
2, 4, 6, 8	Intermediate values	Used to represent compromise between the priorities listed previously

A fuzzy number can always be given by its corresponding left and right representation of each degree of membership:

$$\tilde{M}=(M^{l(y)},M^{r(y)})=(l+(m-l)y,u+(m-u)y),\quad y\in[0,1] \qquad (2)$$

where $l(y)$ and $r(y)$ denote the left side representation and the right side representation of a fuzzy number, respectively. Many ranking methods for fuzzy numbers have been developed in the literature. These methods may provide different ranking result, and most of them are tedious in graphic manipulation requiring complex mathematical calculation (Kahraman et al., 2002).

Fuzzy AHP

The AHP has a special concern with departure from consistency and the measurement of this departure, and with dependence within, and between, the groups of elements of its structure; it has found its widest applications in multi-criteria decision-making in planning and resource allocation, and in conflict resolution. In its general form, the AHP is a non-linear framework for carrying out both deductive and inductive thinking without the use of syllogisms. This is made possible by taking several factors into consideration simultaneously, allowing for dependence and for feedback and making numerical trade-offs to arrive at a synthesis or conclusion (Saaty and Vargas, 2006).

The AHP techniques form a framework of the decisions that uses a one-way hierarchical relation with respect to decision layers. The hierarchy is constructed in the middle level(s), with decision alternatives at the bottom, as shown in Figure 2. The AHP method provides a structured framework for setting priorities on each level of the hierarchy using pair-wise comparisons that are quantified using a 1 to 9 scale as demonstrated in Table 1.

Inability of AHP to deal with the impression and

Table 2. The 1-9 Fuzzy conversion scale

Importance intensity	Triangular fuzzy scale
1	(1, 1, 1)
2	(1.6, 2.0, 2.4)
3	(2.4, 3.0, 3.6)
4	(3.2, 4.0, 4.8)
5	(4.0, 5.0, 6.0)
6	(4.8, 6.0, 7,2)
7	(5.6, 7.0, 8.4)
8	(6.4, 8.0, 9.6)
9	(7.2, 9.0, 10.8)

subjectiveness in the pair-wise comparison process has been improved in fuzzy AHP. Instead of a crisp value, fuzzy AHP a range of value to incorporate the decision maker's uncertainly (Kuswandari, 2004). In this method, the fuzzy conversion scale is shown in Table 2. This scale will be used in Mikhailov (2003) fuzzy prioritization approach.

Data envelopment analysis (DEA)

DEA has been successfully employed for assessing the relative performance of a set of firms, usually called DMUs, which use a variety of identical inputs. The concept of Frontier analysis, suggested by Farrel (1957), forms the basis of DEA, but the recent series of discussions started with an article by Charnes et al.(1978).

DEA is a method for mathematically comparing different (DMUs) productivity based on multiple inputs and outputs. The ratio of weighted inputs and outputs produces a single measure of productivity called relative efficiency. DMUs that have a ratio of 1 are referred to as efficient, given the required inputs and produced outputs. The units that have a ratio less than 1 are less efficient relative to the most efficient units. Because the weights for the input and the output variables of DMUs are computed to maximize the ratio, and then compared to a similar ratio of the best-performing DMUs, the measured productivity is also referred to as relative efficiency.

DEA is a non-parametric approach that does not require any assumptions about the functional form of the production function. About 1000 articles have been written on the subject (Seiford, 1996), providing numerous examples and further development of the model. In the simplest case of a unit having a single input and output, efficiency is defined as the ratio of output/input. DEA deals with units having multiple inputs and outputs that can be incorporated into an efficiency measure where the weighted sum of outputs is divided by the weighted sum of inputs (Friedman and Sinuany-Sterm, 1998).

DEA usually deals with *K* units having multiple inputs X_{ik} and multiple outputs Y_{ik} it can be incorporated into an efficiency measure, which is the weighted sum of the outputs divided by the weighted sum of the inputs e_k. This definition requires a set of factor weights u_r and v_i (Sinuany et al. 2000).

$$e_k = Max\sum_{r=1}^{t} u_r y_{rk} / \sum_{i=1}^{m} v_i x_{ik} \quad (3)$$

s.t:

$$\sum_{r=1}^{t} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \leq 1, \; j = 1, 2, ..., n \quad (4)$$

$$u_r \geq 0, r = 1, 2, ..., t$$
$$v_i \geq 0, i = 1, 2, ..., m$$

In short, the model divides the units into two groups, efficient ($e_k = 1$) and inefficient ($e_k < 1$), by identifying the essence of DEA.

THE PROPOSED DEA- FUZZY AHP METHOD

There are many fuzzy AHP methods proposed by various authors (Buckley, 1985a, b; Chang, 1992, 1996, 1997, 1999; Mikhailov, 2003). These methods are systematic approaches to the alternative selection and justification problem by using the concepts of the fuzzy set theory and hierarchical structure analysis. Decision-makers usually find it is more confident to pass interval judgments than fixed-value judgments.

There have been several attempts to integrate them in real applications and thus, the idea of combining the AHP and DEA is not new. In the current paper, we used the two-stage ranking model AHP/DEA, which combine DEA and AHP. Sinuany-Stern et al. (2000) presented an AHP/DEA methodology for fully ranking organizational units with multiple inputs and multiple outputs. The suggested AHP/DEA methodology was composed of two main stages. In the first stage, the DEA was run for each pair of units separately to create a pairwise comparison matrix. In the second stage, the pairwise comparison matrix created in the first stage was utilized for fully ranking the units via the AHP. The advantage of the AHP/DEA methodology was that the AHP pairwise comparisons were derived mathematically from the input/output data by running pairwise DEA models and there was no subjective evaluation involved in the methodology (Sinunay –Stern et al., 2000) .

In this study, the Fuzzy AHP and DEA for efficiency measurement have advantages over other fuzzy AHP approaches. The priorities obtained from the fuzzy AHP method based on the DEA are defined as a two-staged approach. In the first stage, the pair-wise comparison of the results obtained from the model is based on the DEA; in the second stage, a whole hierarchy is carried out by the fuzzy AHP method on the results obtained from the first stage.

First stage (DEA pair-wise comparisons)

Initially, *K* (*k* = 1, 2... *n*) items of decision-making units are measured at the same time in this evaluation. Each unit has *m* inputs and *s* outputs, where x_{ik} an input of unit k is and y_{rk} is an output *r* of unit *k*. In the DEA-FAHP hybrid model, a binary comparison in decision-making units is carried out. For instance, DMUs are used for the production of x_{ik} (*i* = 1, 2,…, *m*) entries and y_{rk} (*r* = 1,2,...,*s*) outputs. *X* ($m \times n$) and *Y* ($s \times n$) are the amounts of the entries and outputs, respectively.

Mathematical (weighted linear) representation of the problem

$$e_{k,k'} = MAX \sum_{r=1}^{s} u_r y_{rk} \qquad (5)$$

Subject to

$$\sum_{i=1}^{m} v_i x_{ik} = 1 \qquad (6)$$

$$\sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ik} \le 0 \qquad (7)$$

$$\sum_{r=1}^{s} u_r y_{rk'} - \sum_{i=1}^{m} v_i x_{ik'} \le 0 \qquad (8)$$

$$u_r \ge 0 \;\; r = 1,2,\ldots,s \;\; v_i \ge 0 \;\; i = 1,2,\ldots,m$$

By solving this mathematical model, $e_{k,k'}$ elements are solved and the binary compared *E* matrix is obtained. ($k' = 1,\ldots,n$, $k = 1,\ldots,n$ and $k \ne k'$). In the second stage of the DEA- Fuzzy AHP method process, a two-level Fuzzy AHP model is given.

Second stage (Fuzzy AHP ranking)

In the second level, based on the pair-wise comparison matrix *E* and after the hierarchy of fuzzy AHP has been developed, the next stage creates matrices considering the interaction between pair-wise items for the factors and sub factors. We modify the selection process to a nine step method procedure, as follows:

Step 1: The calculation of $a_{k,k'}$: The components of the pair-wise comparative matrix are obtained via the following formula.

$$a_{k,k'} = \frac{e_{k,k'}}{e_{k',k}} \qquad (9)$$

Step 2: The calculation of triangular fuzzy numbers: We setup the triangular fuzzy numbers and each expert makes a pair-wise comparison of the decision criteria and gives them relative scores.

$$\widehat{G}_1 = (l_i, m_i, u_i) \qquad (10)$$

***Step 3*:** The calculation of $\widehat{G}_1$: After establishing triangular fuzzy numbers, we setup the triangular fuzzy numbers using the ANP method based on the fuzzy numbers. Each expert makes a pair-wise comparison of the decision criteria and gives them relative scores.

$$\widehat{G}_1 = (l_i, m_i, u_i) \qquad (11)$$

$$l_i = (l_{i1} \otimes l_{i2} \otimes \ldots \otimes l_{ik})^{1/k} \qquad i = 1,2,\ldots,k \qquad (12)$$

$$m_i = (m_{i1} \otimes m_{i2} \otimes \ldots \otimes m_{ik})^{1/k} \qquad i = 1,2,\ldots,k \qquad (13)$$

$$u_i = (u_{i1} \otimes u_{i2} \otimes \ldots \otimes u_{ik})^{1/k} \qquad i = 1,2,\ldots,k \qquad (14)$$

***Step 4*:** The calculation of $\widehat{G}_T$: The geometric fuzzy mean of the total row is established using:

$$\widehat{G}_T = (\sum_{i=1}^{k} l_i, \sum_{i=1}^{k} m_i, \sum_{i=1}^{k} u_i) \qquad (15)$$

Step 5: The calculation of $\widehat{G}_T$: Fuzzy geometric mean of the fuzzy priority value calculated with normalization priorities for factors using:

$$\tilde{w} = \tilde{G}_i / \tilde{G}_T = (l_i, m_i, u_i) / \left(\sum_{i=1}^{k} l_i, \sum_{i=1}^{k} m_i, \sum_{i=1}^{k} u_i\right) = \left[\frac{l_i}{\sum_{i=1}^{k} u_i}, \frac{m_i}{\sum_{i=1}^{k} m_i}, \frac{u_i}{\sum_{i=1}^{k} l_i}\right] \quad (16)$$

Step 6: The calculation of $wi_{\alpha l}$: Factors belonging to nine different *α-cut* values α for the calculated, fuzzy priorities will be applied for lower and upper limits for each α value:

$$wi_{\alpha l} = (wil_{\alpha l}, wiu_{\alpha l}) \quad i = 1,2,...,k \quad l = 1,2,...,L \quad (17)$$

Step 7: The calculation of W_{il}, W_{iu}: Combine the entire upper values and the lower values α seperately than divide than by total sum of the value:

$$W_{il} = \frac{\sum_{i=1}^{L} \alpha (w_{il})_l}{\sum_{l=1}^{L} \alpha_l} \quad i = 1,2,...,k \quad l = 1,2,...,L \quad (18)$$

$$W_{iu} = \frac{\sum_{i=1}^{L} \alpha (w_{iu})_l}{\sum_{l=1}^{L} \alpha_l} \quad i = 1,2,...,k \quad l = 1,2,...,L \quad (19)$$

Step 8: The calculation of w_{id}: Use the following formula in order to defuzzification by the Combine upper limit value and lower limit value using the optimism index (λ)

$$w_{id} = \lambda W_{iu} + (1-\lambda) W_{il} \quad \lambda \in [0,1] \quad i = 1,2,...,k \quad (20)$$

Step 9: The calculation of W_{in}: Normalization defuzzification value priorites using

$$W_{in} = \frac{w_{id}}{\sum_{i=1}^{k} w_{id}} \quad i = 1,\ldots,k \quad (21)$$

APPLYING THE SEQUENTIAL HYBRID METHODOLOGY

Data and sample

The suggested model demonstrated an example of a selected unit supported by a University Turkey, which is a comprehensive public university. Fiften departments have been considered in our evaluation. In our study a six-input evaluation criteria and four-output evaluation criteria:

Inputs

The inputs of this study are a number of Professor Doctors, Associated Professor, Assistant Professor, and Instructors- Budget of departments- and Number of credits.

Outputs

The outputs of this study are a number of alumni (undergraduates and graduate students), Evaluation of instructors, Number of academic congeries; and Number of academic papers (SCI-SSCI-AHCI).

The result score is always the-bigger-the-better. As visible in Table 3, departmrnt 3 has the largest score due to its highest efficiency and performance. Department 11 has the smallest score of the fifteen units, and is ranked in the last place. The relevant results can be seen in Table 3. Obviously, the best selection is candidate D3.

CONCLUSION

Both DEA and Fuzzy AHP methods are commonly used in practice and, yet, both have limitations. The hybrid model DEA-Fuzzy AHP combines the best of both models by avoiding the pitfalls of each. Therefore, we have presented an effective model for rank scaling of the units with multiple inputs and multiple outputs using both DEA and Fuzzy AHP to evaluate the performance of department a University located in Turkey in this paper. A two-stage hybrid methodology is provided where the binary comparison of the results obtained from the model is based on DEA. The second stage of the methodology assists in fully-ranking of the alternatives based on the results obtained from the first stage. The result of the methodology is a rank order of the alternatives, which can be used to select an individual project or a portfolio of projects. Furthermore, in this model, we work with given tangible inputs and outputs of units, and no subjective assessment of decision maker's evaluation is involved. The Pareto optimum limitation of DEA is resolved by the fully- ranking performed here by means of Fuzzy AHP. It is important to note that DEA-fuzzy AHP does not replace DEA, but that it provides further analysis of DEA to fully rank the units.

The performance measurement model developed here structures the performance measurement problem in a hierarchical form, critical areas, and performance

Table 3. The DEA-fuzzy AHP fully-rank score

DMU	DEA-fuzzy AHP score
D1	0.06671
D2	0.06671
D3	0.06673
D4	0.06671
D5	0.06671
D6	0.06671
D7	0.06671
D8	0.06671
D9	0.06671
D10	0.06671
D11	0.06634
D12	0.06671
D13	0.06671
D14	0.06671
D15	0.06671

measures. The developed performance measurement model contributes to the previous performance measurement models by including and quantifying inter dependencies that exist between system components. Besides, the involvement of the fuzzy theory can adequately resolve the inherent uncertainty and imprecision associated with the mapping of a decision maker's perception to exact numbers. For the future research, the authors suggest the other multicriteria approaches such as DEA and Intuitionistic fuzzy TOPSIS outranking methods to be used and to be compared in justification of the selection problem.

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