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An Integrated Approach of Fuzzy ANP and Fuzzy TOPSIS for R&D Project Selection: A Case Study

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Abstract: This paper presents an integrated fuzzy approach for selecting R&D project. In the integrated approach, fuzzy concepts are used for decision-makers' subjective judgments to reflect the vague nature of the selection process. Fuzzy ANP and Fuzzy TOPSIS are included in the integrated approach. Fuzzy ANP is used to determine the fuzzy weights of criteria and sub-criteria. Fuzzy TOPSIS aims to rank projects with respect to the sub-criteria. We apply the integrated approach in real case to demonstrate the application of the proposed method.

Key words: Analytical network process (ANP), TOPSIS, Fuzzy set, Research and development (R&D).

INTRODUCTION

For many firms, especially those that depend on innovation to stay in business, the key to continued competitiveness lies in their ability to develop and implement new products and processes. For these organizations, research and development (R&D) is an integral function within the strategic management framework (Meade *et al*., 2002). R&D projects must be compatible with the company's vision and mission. The predominant objective of undertaking such projects is to develop new products and processes so as to compete in dynamic markets. The challenging tasks involve enabling the organization to choose the right projects, i.e. projects that will lead to success and provide the organization a prioritized list of projects that will improve the chance of success and will have futuristic scope. Nowadays, most companies are concerned with the scientific selection of R&D projects. R&D project selection is a crucial task. It is a complicated decision-making process with features of multiple stages, multiple groups of decision-makers, multiple and often-conflicting objectives, and high risk and uncertainty in predicting the future success and impacts (Ghasemzadeh and Archer, 2000). Considerable effort has been made in the past several years to help organizations make better decisions in R&D project selection (Martino 1995, Henriksen and Traynor 1999, Ghasemzadeh and Archer 2000, Ibbs and Kwak 2000, Ringuest *et al*., 2000, 2004, Klapka and Pinos 2002, Osawa and Murakami 2002, Tian *et al*., 2002a, b, c, Lawson *et al*., 2004). Most of these studies focus on building decision models and developing decision-making methods. Traditionally, companies use three elements in the selection process: eligibility assessment, scoring using the selection criteria and qualitative appraisal. Henriksen and Traynor (1999) reviewed the literature and classified current decision models and methods into the following categories: unstructured peer review, scoring, mathematical programming, economic model, decision analysis, interactive method, artificial intelligence, and portfolio optimization. To improve the usability of these decision models and methods, current research efforts are deploying decision support systems to support the R&D project selection tasks (Bard *et al*., 1988, Liberatore 1988a, b, Iyigun 1993, Liberatore and Stylianou 1995, Ghasemzadeh and Archer 2000, William and Young 2003, Tiana *et al*., 2005a, b). The rest of the paper is organized as follows: The following section presents a concise treatment of the basic concepts of fuzzy set theory. Section 3 presents the methodology of fuzzy ANP and fuzzy TOPSIS. The application of the proposed framework to R&D project selection is addressed in Section 4. Finally, conclusions are provided in Section 5.

2. Fuzzy Set Theory:

Fuzzy set theory was first developed in 1965 by Zadeh; he was attempting to solve fuzzy phenomenon problems, including problems with uncertain, incomplete, unspecific, or fuzzy situations. Fuzzy set theory is more advantageous than traditional set theory when describing set concepts in human language. It allows us to address unspecific and fuzzy characteristics by using a membership function that partitions a fuzzy set into subsets of members that ''incompletely belong to" or ''incompletely do not belong to" a given subset.

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2.1. Fuzzy Numbers:

We order the Universe of Discourse such that U is a collection of targets, where each target in the Universe of Discourse is called an element. Fuzzy number $\widetilde{A}$ is mapped onto U such that a random $x \rightarrow U$ is appointed a real number, $\mu_{\widetilde{A}}(x) \rightarrow [0,1]$. If another element in U is greater than x, we call that element under A.

The universe of real numbers R is a triangular fuzzy number (TFN)$\widetilde{A}$, which means that for $x \in R, \mu_{\widetilde{A}}(x) \in [0,1]$, and

$$\mu_{\widetilde{A}}(x) = \begin{cases} (x-L)/(M-L), & L \leq x \leq M, \\ (U-x)/(U-M), & M \leq x \leq U, \\ 0, \quad \text{otherwise}, \end{cases}$$

Note that $\widetilde{A} = (L, M, U)$, where L and U represent fuzzy probability between the lower and upper boundaries, respectively, as in Fig. 1. Assume two fuzzy numbers $\widetilde{A}_1 = (L_1, M_1, U_1)$, and $\widetilde{A}_2 = (L_2, M_2, U_2)$; then,

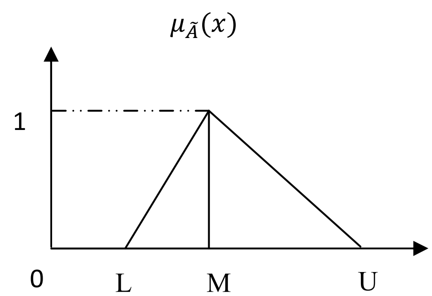

Fig. 1: Triangular fuzzy number.

(1) $\widetilde{A}_1 \oplus \widetilde{A}_2 = (L_1, M_1, U_1) \oplus (L_2, M_2, U_2) = (L_1 + L_2, M_1 + M_2, U_1 + U_2)$

(2) $\widetilde{A}_1 \otimes \widetilde{A}_2 = (L_1, M_1, U_1) \otimes (L_2, M_2, U_2) = (L_1 L_2, M_1 M_2, U_1 U_2), L_i > 0, M_i > 0, U_i > 0$

(3) $\widetilde{A}_1 - \widetilde{A}_2 = (L_1, M_1, U_1) - (L_2, M_2, U_2) = (L_1 - L_2, M_1 - M_2, U_1 - U_2)$

(4) $\widetilde{A}_1 \div \widetilde{A}_2 = (L_1, M_1, U_1) \div (L_2, M_2, U_2) = \left(\frac{L_1}{L_2}, \frac{M_1}{M_2}, \frac{U_1}{U_2}\right), L_i > 0, M_i > 0, U_i > 0$

(5) $\widetilde{A}_1^{-1} = (L_1, M_1, U_1)^{-1} = \left(\frac{1}{U_1}, \frac{1}{M_1}, \frac{1}{L_1}\right), L_i > 0, M_i > 0, U_i > 0$

2.2. Fuzzy Linguistic Variables:

The fuzzy linguistic variable is a variable that reflects different aspects of human language. Its value represents the range from natural to artificial language. When the values or meanings of a linguistic factor are being reflected, the resulting variable must also reflect appropriate modes of change for that linguistic factor. Moreover, variables describing a human word or sentence can be divided into numerous linguistic criteria, such as equally important, moderately important, strongly important, very strongly important, and extremely important, as shown in Fig. 2; definitions and descriptions are shown in Table 1. For the purposes of the present study, the 5-point scale (equally important, moderately important, strongly important, very strongly important and extremely important) is used.

3. Research Methodology:

In this paper, the weights of each criterion are calculated using fuzzy ANP. After that, fuzzy TOPSIS is utilized to rank the alternatives. Finally, we select the best project based on these results.

3.1. Analytic Network Process:

The purpose of the ANP approach is to solve problems involving interdependence and feedback among criteria or alternative solutions. ANP is the general form of the analytic hierarchy process (AHP), which has been used in multi-criteria decision-making (MCDM) in order to consider non-hierarchical structures. MCDM has been applied to project selection, product planning, and so forth (Ong, Huang, & Tzeng, 2004).

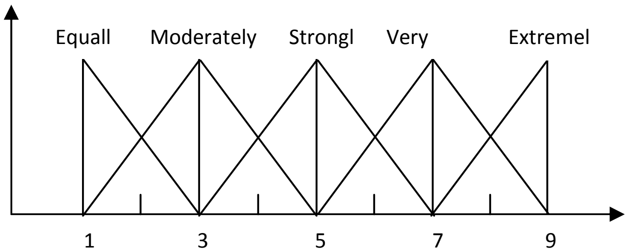

Fig. 2: A fuzzy membership function for linguistic variable attributes.

Table 1: Definition and membership function of fuzzy number.

Fuzzy number	Linguistic variable	Triangular fuzzy number
$\tilde{9}$	Extremely important/preferred	(7,8,9)
$\tilde{7}$	Very strongly important/preferred	(5,6,7)
$\tilde{5}$	Strongly important/preferred	(4,5,6)
$\tilde{3}$	Moderately important/preferred	(2,3,4)
$\tilde{1}$	Equally important/preferred	(1,2,3)

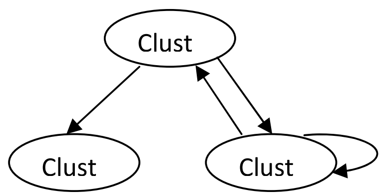

Fig. 3: Case 1 structure.

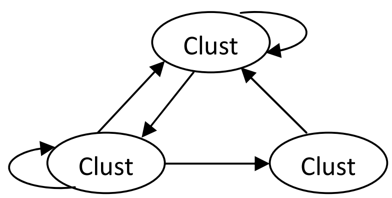

Fig. 4: Case 2 structure.

The first phase of ANP compares the measuring criteria in the overall system to form a super matrix. This can be accomplished using pair-wise comparisons. The relative importance-values of pair-wise comparisons can be categorized from 1 to 9 in order to represent pairs of equal importance (1) to extreme inequality in importance (9) (Saaty, 1980). The following is the general form of the super matrix (Liou *et al*., 2007):

$$\boldsymbol{W} = \begin{array}{c} \\ C_1 \begin{array}{c} e_{11} \\ e_{12} \\ \vdots \\ e_{1m_1} \end{array} \\ C_2 \begin{array}{c} e_{21} \\ e_{22} \\ \vdots \\ e_{2m_2} \end{array} \\ \vdots \\ C_n \begin{array}{c} e_{n1} \\ e_{n2} \\ \vdots \\ e_{nm_n} \end{array} \end{array} \begin{array}{c} \begin{array}{cccc} \begin{array}{c} C_1 \\ e_{11}\ldots e_{1m_1} \end{array} & \begin{array}{c} C_2 \\ e_{21}\ldots e_{2m_2} \end{array} & \cdots\cdots & \begin{array}{c} C_n \\ e_{n1}\ldots e_{nm_n} \end{array} \end{array} \\ \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{12} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix} \end{array}$$

Where c_m denotes the mth cluster, e_{mn} denotes the mth element in the mth cluster; and W_{ij} is the principal eigenvector of the influence of the elements compared in the jth cluster to the ith cluster. In addition, if the jth cluster has no influence to the jth cluster, then $W_{ij} = 0$.

Thus, the form of the super matrix relies on the variety of its structure. There are several structures that were proposed by Saaty including hierarchy, holarchy, suparchy, and so on (Ong *et al*., 2004). In order to demonstrate how the structure is affected by the super matrix, Ong *et al* (2004) offer two simple cases that both involve three clusters to show how to form the super matrix in accordance with different structures (see Fig. 3).

Based on Fig. 3, the super matrix can be formed as:

$$W = \begin{matrix} & C_1 & C_2 & C_3 \\ C_1 \\ C_2 \\ C_3 \end{matrix} \begin{bmatrix} 0 & 0 & W_{13} \\ W_{21} & 0 & 0 \\ W_{31} & 0 & W_{33} \end{bmatrix}$$

In Fig. 4, a case more complex than that depicted in Fig. 3 is shown. Based on Fig. 4, the super matrix can be formed as:

$$W = \begin{matrix} & C_1 & C_2 & C_3 \\ C_1 \\ C_2 \\ C_3 \end{matrix} \begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & 0 \end{bmatrix}$$

After forming the super matrix, the weighted super matrix is generated by transforming all column sums to unity (Ong *et al*., 2004).

Then, we use the weighted super matrix to generate a limiting super matrix by using Eq. (1) to calculate global weights.

$$\lim_{k\to\infty} \boldsymbol{W}^k \quad (1)$$

In this step, if the super matrix shows signs of cyclicity, then there exists more than one limiting super matrix. That is, there are two or more limiting super matrices, and the Cesaro sum must be calculated to obtain the priority among these matrices. The Cesaro sum is calculated using Eq. (2).

$$\lim_{k\to\infty} \left(\frac{1}{N}\right) \sum_{k=1}^{N} \boldsymbol{W}^k \quad (2)$$

Eq. (2) calculates the average effect of a limiting super matrix; otherwise, the super matrix can be raised to a large power to generate the priority weights.

The steps of the fuzzy ANP calculation are provided as follow:

Step 1: Confirm both dimensions and criteria of the model.

Step 2: Develop the ANP model hierarchically using the dimensions, and criteria.

Step 3: Determine the local weights of both dimensions and criteria by utilizing pair-wise comparison matrices. Assume that there is no dependence between each. The relative importance-values of pair-wise comparisons are provided in Table 1.

Step 4: Determine the inner dependence matrix of each dimension with respect to other dimensions. In Step 3, the dependence of local weights in the inner matrix was calculated, such that this step is intended to calculate the interdependent weights of the dimensions.

Step 5: Calculate the global weights for the sub-factors. This can be done by multiplying the local weight of each sub-factor with the interdependent weights associated with dimensions where it belongs.

3.2. The Fuzzy Topsis Method:

TOPSIS views a MADM problem with *m* alternatives as a geometric system with *m* points in the *n*-dimensional space. The method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. TOPSIS defines an index called similarity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution (Wang & Chang, 2007). It is often difficult for a decision-maker to assign a precise performance rating to an alternative for the attributes under consideration. The merit of using a fuzzy approach is to assign the relative importance of attributes using fuzzy numbers instead of precise numbers. This section extends the TOPSIS to the fuzzy environment (Yang & Hung, 2007). This method is particularly suitable for solving the group decision-making problem under fuzzy environment. We briefly review the rationale of fuzzy theory before the development of fuzzy TOPSIS. The mathematics concept borrowed from Ashtiani, Haghighirad, Makui, and Montazer (2008), (Büyüközkan *et al*., 2007) and (Wang and Chang, 2007).

Step 1: Determine the weighting of evaluation criteria.

A systematic approach to extend the TOPSIS is proposed to selecting under a fuzzy environment in this section. In this paper the importance weights of various criteria and the ratings of qualitative criteria are considered as linguistic variables (as Table 1) (Chen, Lin, & Huang, 2006).

Step 2: Construct the fuzzy decision matrix and choose the appropriate linguistic variables for the alternatives with respect to criteria

$$\widetilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_N \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \quad i=1,2,\dots,m;\ j=1,2,\dots,n$$

$$\tilde{x}_{ij} = \frac{1}{k}\,(\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{k}\ ) \qquad (3)$$

where $\widetilde{x}_{ij}^{k}$ is the rating of alternative A_i with respect to criterion C_j evaluated by expert and

$\tilde{x}_{ij}^{k} = (a_{ij}^{k}\ , b_{ij}^{k}, c_{ij}^{k})$

Step 3: Normalize the fuzzy decision matrix

The normalized fuzzy decision matrix denoted by $\widetilde{R}$ is shown as following formula:

$$\widetilde{R} = [\tilde{r}_{ij}]_{m\times n}\ ,\ i= 1,2,\dots,m;\ j=1,2,\dots,n \qquad (4)$$

Then the normalization process can be performed by following formula:

Where $\tilde{r}_{ij} = (\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+})$ $c_j^+ = \max_i c_{ij}$

The normalized $\widetilde{r}_{ij}$ are still triangular fuzzy numbers. For trapezoidal fuzzy numbers, the normalization process can be conducted in the same way. The weighted fuzzy normalized decision matrix is shown as following matrix $\widetilde{V}$:

$$\tilde{v} = [\tilde{v}_{ij}]_{m\times n}\ ,\ i= 1,2,\dots,m;\ j=1,2,\dots,n \qquad (5)$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \widetilde{w}_j \qquad (6)$$

Step 4: Determine the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS)

According to the weighted normalized fuzzy decision matrix, we know that the elements $\widetilde{V}_{ij}$ are normalized positive TFNs and their ranges belong to the closed interval [0, 1]. Then, we can define the FPIS A^+ and FNIS A^- as following formula:

$$A^{+}= (\widetilde{V}_1^{+}\ , \widetilde{V}_2^{+}\ ,\dots, \widetilde{V}_n^{+}\ ) \qquad (7)$$

$$A^{-}= (\widetilde{V}_1^{-}\ , \widetilde{V}_2^{-}\ ,\dots, \widetilde{V}_n^{-}\ ) \qquad (8)$$

where $\widetilde{V}_j^{+} = (1,1,1)$ and $\widetilde{V}_j^{-} = (0,0,0)$ $j=1,2,\dots,n$

Step 5: Calculate the distance of each alternative from FPIS and FNIS

The distances (d_i^+ and d_i^-) of each alternative A^+ from and A^- can be currently calculated by the area compensation method.

$$d_i^+ = \sum_{j=1}^{n} d(\ \tilde{v}_{ij}, \widetilde{V}_j^{+}\ )\ ,\ i=1,2,\dots,m \quad j=1,2,\dots,n \qquad (9)$$

$$d_i^- = \sum_{j=1}^{n} d(\ \tilde{v}_{ij}, \widetilde{V}_j^{-}\ )\ ,\ i=1,2,\dots,m \quad j=1,2,\dots,n \qquad (10)$$

Step 6: Obtain the closeness coefficient and rank the order of alternatives

The CC_i is defined to determine the ranking order of all alternatives once the d_i^+ and d_i^- of each alternative have been calculated. This step solves the similarities to an ideal solution by formula:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i=1,2,\dots,m \qquad (11)$$

According to the CC_i, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives. In the last years, some fuzzy TOPSIS methods were developed in the different applied field. Lin and Chang (2008) adopted fuzzy TOPSIS for order selection and pricing of manufacturer (supplier) with make-to-order basis when orders exceed production capacity. Chen and Tsao (2008) are to extend the TOPSIS method based on interval-valued fuzzy sets in decision analysis. Ashtiani *et al*. (2008) used interval-valued fuzzy TOPSIS method is aiming at solving MCDM problems in which the weights of criteria are unequal, using interval-valued fuzzy sets concepts. Mahdavi, Mahdavi-Amiri, Heidarzade, and Nourifar (2008) designed a model of TOPSIS for the fuzzy environment with the introduction of appropriate negations for obtaining ideal solutions. Büyüközkan *et al*. (2007) identified the strategic main and sub-criteria of alliance partner selection that companies consider the most important through Fuzzy AHP and fuzzy TOPSIS model and achieved the final partner-ranking results. Abo-Sinna, Amer, and Ibrahim (2008) focused on multi-objective large-scale non-linear programming problems with block angular structure and extended the technique for order preference by similarity ideal solution to solve them. Wang and Chang (2007) applied fuzzy TOPSIS to help the Air Force Academy in Taiwan choose optimal initial training aircraft in a fuzzy environment. Li (2007) developed a compromise ratio (CR) methodology for fuzzy multi-attribute group decision making (FMAGDM), which is an important part of decision support system. Wang and Lee (2007) generalized TOPSIS to fuzzy multiple-criteria group decision-making (FMCGDM) in a fuzzy environment. Kahraman, Çevik, Ates, and Gülbay (2007) proposed a fuzzy hierarchical TOPSIS model for the multi-criteria evaluation of the industrial robotic systems. Benı´tez, Martı´n, and Román (2007) presented a fuzzy TOPSIS approach for evaluating dynamically the service quality of three hotels of an important corporation in Gran Canaria island via surveys. Wang and Elhag (2006) proposed a fuzzy TOPSIS method based on alpha level sets and presents a non-linear programming solution procedure. Chen *et al*. (2006) applied fuzzy TOPSIS approach to deal with the supplier selection problem in supply chain system.

4. A Numerical Application Of Proposed Approach:

The proposed approach is applied in a manufacturing company, located in Qom, Iran. Through the literature investigation and studying other papers that are related to R&D project selection, finally four main criteria and twenty subcritical are selected. The research framework is shown in Fig 5. This research framework includes four main criteria, such as Project attributes, Organizational attributes, Market attributes and Environmental attributes. Subcritical for Project attribute includes the expected utility of the project (P_1), strategic need (P_2), product life before obsolescence (P_3), potential technical interaction with existing products (P_4), and potential market interactions with existing products (P_5). Subcritical for Organizational attributes are includes competence and experience on similar project (O_1), knowledge / skills availability (O_2), the research staff available (O_3), raw material availability (O_4) and facilities available (O_5). Subcritical for Market attributes are includes potential market size (M_1), expected market share (M_2), degree of competition in a similar field (M_3), competitors efforts in similar areas (M_4) and net present value (M_5). Subcritical for Environmental attributes encompasses government policies (E_1), economic regulations (E_2), social ambiance (E_3), safety considerations (E_4) and environmental considerations (E_5). In addition, there are four alternatives include A_1, A_2, A_3 and A_4.

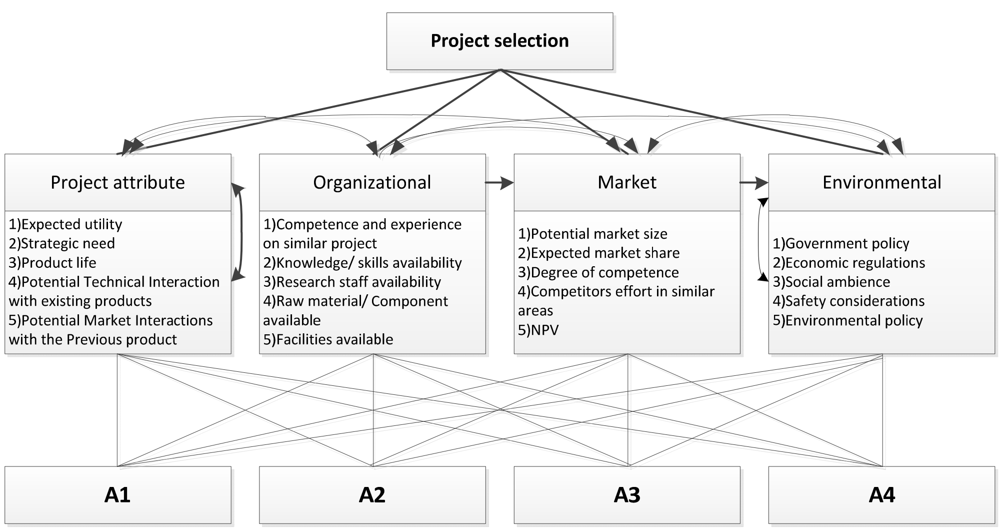

Fig. 5. Research framework.

In this paper, the weights of criteria are calculated by using fuzzy-ANP, and these calculated weight values are used as Fuzzy TOPSIS inputs. Then, after Fuzzy TOPSIS calculations, evaluation of the alternatives and selection of the most appropriate project is realized.

Fuzzy ANP:

In fuzzy-ANP, firstly, we should determine the weights of each subcriterion by utilizing pair-wise comparison matrices. We compare each subcritical with respect to other subcritical because of inner dependence. You can see the pair-wise comparison matrices for Project attributes as an example in Table 2,3,4,5 and Table 6.

Table 2: pair-wise comparison of subcritical with respect to P_1.

P_1	P_2	P_3	P_4	P_5	weight
P_2	(1,1,1)	(1,2,3)	(2,3,4)	(.33,.5,1)	0.311165
P_3	(.33,.5,1)	(1,1,1)	(1,2,3)	(2,3,4)	0.311165
P_4	(.25,.33,1.5)	(.33,.5,1)	(1,1,1)	(.33,.5,1)	0.105611
P_5	(1,2,3)	(.25,.33,.5)	(1,2,3)	(1,1,1)	0.27206

Table 3: pair-wise comparison of subcritical with respect to P_2.

P_2	P_1	P_3	P_4	P_5	weight
P_1	(1,1,1)	(1,2,3)	(.33,.5,1)	(2,3,4)	0.301583
P_3	(.33,.5,1)	(1,1,1)	(2,3,4)	(1,2,3)	0.301583
P_4	(1,2,3)	(.25,.33,.5)	(1,1,1)	(.33,.5,1)	0.198417
P_5	(.25,.33,.5)	(.33,. 5,1)	(1,2,3)	(1,1,1)	0.198417

Table 4: pair-wise comparison of subcritical with respect to P_3.

P_3	P_1	P_2	P_4	P_5	weight
P_1	(1,1,1)	(1,2,3)	(2,3,4)	(.25,.33,.5)	0.294087
P_2	(.33,.5,1)	(1,1,1)	(1,2,3)	(.33,.5,1)	0.209885
P_4	(.25,.33,.5)	(.33,.5,1)	(1,1,1)	(1,2,3)	0.196841
P_5	(2,3,4)	(1,2,3)	(.33,.5,1)	(1,1,1)	0.299187

Table 5: pair-wise comparison of subcritical with respect to P_4.

P_4	P_1	P_2	P_3	P_5	weight
P_1	(1,1,1)	(2,3,4)	(.33,.5,1)	(2,3,4)	0.336537
P_2	(.25,.33,.5)	(1,1,1)	(1,2,3)	(1,2,3)	0.257382
P_3	(1,2,3)	(.33,.5,1)	(1,1,1)	(.25,.33,.5)	0.178267
P_5	(.25,.33,.5)	(.33,.5,1)	(2,3,4)	(1,1,1)	0.227813

Table 6: pair-wise comparison of subcritical with respect to P_5.

P_5	P_1	P_2	P_3	P_4	weight
P_1	(1,1,1)	(1,2,3)	(.33,.5,1)	(2,3,4)	0.322846
P_2	(.33,.5,1)	(1,1,1)	(1,2,3)	(2,3,4)	0.322846
P_3	(1,2,3)	(.33,.5,1)	(1,1,1)	(2, 3,4)	0.322846
P_4	(.25,.33,.5)	(.25,.33,.5)	(.25,.33,.5)	(1,1,1)	0.031461

In the next step, initial supermatrix is calculated and after that we normalized the initial supermatrix that is shown in Table 7.

Table 7: The normalized supermatrix.

w'		Project attribute					Organizational					…	Environmental		
		P_1	P_2	P_3	P_4	P_5	O_1	O_2	O_3	O_4	O_5	…	E_3	E_4	E_5
Project attribute	P_1	0.17	0.07	0.04	0.05	0.05	0.25	0.11	0.05	0.08	0.07	…	0.00	0.00	0.00
	P_2	0.06	0.17	0.02	0.05	0.05	0.04	0.25	0.07	0.06	0.06	…	0.00	0.00	0.00
	P_3	0.09	0.08	0.17	0.07	0.04	0.09	0.07	0.25	0.06	0.10	…	0.00	0.00	0.00
	P_4	0.00	0.01	0.06	0.17	0.02	0.06	0.04	0.08	0.25	0.02	…	0.00	0.00	0.00
	P_5	0.01	0.01	0.05	0.01	0.17	0.06	0.03	0.05	0.05	0.25	…	0.00	0.00	0.00
Organizational	O_1	0.17	0.04	0.11	0.07	0.04	0.00	0.00	0.00	0.00	0.00	…	0.04	0.06	0.05
	O_2	0.10	0.17	0.04	0.03	0.03	0.00	0.00	0.00	0.00	0.00	…	0.05	0.04	0.04
	O_3	0.03	0.07	0.17	0.03	0.07	0.00	0.00	0.00	0.00	0.00	…	0.17	0.03	0.05
	O_4	0.01	0.03	0.01	0.17	0.02	0.00	0.00	0.00	0.00	0.00	…	0.03	0.17	0.03
	O_5	0.02	0.02	0.01	0.03	0.17	0.00	0.00	0.00	0.00	0.00	…	0.05	0.04	0.17
Market	M_1	0.17	0.07	0.05	0.11	0.05	0.00	0.00	0.00	0.00	0.00	…	0.05	0.06	0.05
	M_2	0.07	0.17	0.04	0.05	0.05	0.00	0.00	0.00	0.00	0.00	…	0.02	0.04	0.05
	M_3	0.04	0.06	0.17	0.00	0.05	0.00	0.00	0.00	0.00	0.00	…	0.17	0.03	0.03
	M_4	0.05	0.02	0.04	0.17	0.02	0.00	0.00	0.00	0.00	0.00	…	0.05	0.17	0.04
	M_5	0.00	0.02	0.03	0.00	0.17	0.00	0.00	0.00	0.00	0.00	…	0.05	0.04	0.17
Environmental	E_1	0.00	0.00	0.00	0.00	0.00	0.25	0.11	0.07	0.07	0.07	…	0.05	0.06	0.05
	E_2	0.00	0.00	0.00	0.00	0.00	0.05	0.25	0.06	0.07	0.07	…	0.03	0.04	0.05
	E_3	0.00	0.00	0.00	0.00	0.00	0.09	0.03	0.25	0.08	0.10	…	0.17	0.03	0.05
	E_4	0.00	0.00	0.00	0.00	0.00	0.05	0.03	0.06	0.25	0.01	…	0.03	0.17	0.01
	E_5	0.00	0.00	0.00	0.00	0.00	0.06	0.07	0.05	0.03	0.25	…	0.05	0.04	0.17

According to Eq. (1), we calculate the final supermatrix and we obtain the weights of each criterion. The final supermatrix is shown in Table 8.

Table 8: The final supermatrix

$(W')^{11}$		Project attribute					Organizational					…	Environmental		
		P_1	P_2	P_3	P_4	P_5	O_1	O_2	O_3	O_4	O_5	…	E_3	E_4	E_5
Project attribute	P_1	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	…	0.07	0.07	0.07
	P_2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	…	0.06	0.06	0.06
	P_3	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	…	0.07	0.07	0.07
	P_4	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
	P_5	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	…	0.05	0.05	0.05
Organizational	O_1	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	…	0.07	0.07	0.07
	O_2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	…	0.06	0.06	0.06
	O_3	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	…	0.06	0.06	0.06
	O_4	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
	O_5	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
Market	M_1	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	…	0.05	0.05	0.05
	M_2	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
	M_3	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
	M_4	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	…	0.03	0.03	0.03
	M_5	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	…	0.03	0.03	0.03
Environmental	E_1	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	…	0.07	0.07	0.07
	E_2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	…	0.06	0.06	0.06
	E_3	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	…	0.07	0.07	0.07
	E_4	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	…	0.04	0.04	0.04
	E_5	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	…	0.05	0.05	0.05

Thus, the weight vector from Table 8 is obtained as

w^t = (0.07, 0.06, 0.07, 0.04, 0.05, 0.07, 0.06, 0.06, 0.04, 0.04,0.05,0.04,0.04,0.03,0.03,0.07,0.06,0.07,0.04,0.05)
T

Fuzzy Topsis:

The weights of the criteria are calculated by fuzzy ANP up to now, and then these values can be used in Fuzzy TOPSIS. So, the Fuzzy TOPSIS methodology must be started at the second step. Thus, weighted normalized decision matrix can be prepared. This matrix can be seen from Table 9.

Table 9: Weighted normalized decision matrix.

	P_1	P_2	P_3	...	E_3	E_4	E_5
A_1	(.13,.25,.63)	(.06,.19,.25)	(.13,.25,.38)	...	(.06,.19,.25)	(.13,.25,.38)	(.38,.50,.63)
A_2	(.25,.63,.88)	(.13,.25,.50)	(.38,.50,.56)	...	(.13,.25,.50)	(.38,.50,.56)	(.13,.25,.38)
A_3	(.13,.25,.38)	(.25,.31,.50)	(.13,.25,.50)	...	(.25,.31,.50)	(.13,.25,.50)	(.38,.50,.56)
A_4	(.38,.50,.75)	(.38,.50,.56)	(.13,.63,1.0)	...	(.38,.50,.56)	(.13,.63,1.0)	(.13,.25,.38)
W	0.07	0.06	0.07	...	0.07	0.04	0.05

In the next step we should determine the fuzzy positive and fuzzy negative-ideal reference points, then we can define the fuzzy positive-ideal solution (FPIS) and the fuzzy negative-ideal solution (FNIS) as: $A^+$and A^-.

A^+ = [(1, 1, 1)]

A^- = [(0, 0, 0)]

In order to calculate the closeness coefficients of each of the alternatives d_i^+ and d_i^- calculation is used as an example as follows. Once the distances of cluster policy from FPIS and FNIS are determined, the closeness coefficient can be obtained with Eq. (11). The index CC_1 of first alternative is calculated as:

d_i^+ = 34.07 d_i^- = 0.73

From the alternative evaluation results in Table 10, the best project is A_4.

$CC_1 = \frac{0.73}{34.07+0.73} = 0.02$

Table 10: Closeness coefficients and ranking.

	P_1	P_2	P_3	...	E_5	d(+)	d(-)	CC_i	rank
A_1	(.01,.02,.05)	(.00,.01,.02)	(.01,.02,.03)	...	(.02,.03,.03)	34.07	0.73	0.02	3
A_2	(.02,.05,.06)	(.01,.02,.03)	(.03,.04,.04)	...	(.01,.01,.02)	33.93	0.84	0.02	2
A_3	(.01,.02,.03)	(.02,.02,.03)	(.01,.02,.04)	...	(.02,.03,.03)	34.05	0.73	0.02	4
A_4	(.03,.04,.05)	(.02,.03,.04)	(.01,.05,.07)	...	(.01,.01,.02)	33.79	0.99	0.03	1

The Fuzzy TOPSIS results are shown in Table 10. The evaluation of R&D project is realized and according to the CC_i values the ranking of projects are A_4– A_2– A_1 – A_3 from most preferable to least. If the best one is needed to be selected, then the alternative A_4 must be chosen.

Conclusions:

Research and development (R&D) project selection is a complex decision-making process. It involves a search of the environment of opportunities, the generation of project options, and the evaluation by different stakeholders of multiple attributes, both qualitative and quantitative. This paper illustrates an application of fuzzy ANP (analytic network process) along with fuzzy TOPSIS in selecting R&D projects. Fuzzy set theory is incorporated to overcome the vagueness in the preferences. A two step fuzzy-ANP and Fuzzy TOPSIS methodology is structured here that Fuzzy TOPSIS uses fuzzy-ANP result weights as input weights. Then a real case is presented to show applicability and performance of the methodology. It can be said that using linguistic variables makes the evaluation process more realistic. Because evaluation is not an exact process and has fuzziness in its body. Here, the usage of fuzzy-ANP weights in Fuzzy TOPSIS makes the application more realistic and reliable. As a future direction, other decision-making methods such as fuzzy ELECTRE, fuzzy GTMA and fuzzy VIKOR can be used in this area.

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