Expert Systems with Applications 40 (2013) 480–491

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A hybrid fuzzy group decision support framework for advanced-technology prioritization at NASA

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ARTICLE INFO

Keywords:
Fuzzy group decision making
Fuzzy ANP
Fuzzy TOPSIS
NASA project assessment

ABSTRACT

The prioritization of advanced-technology projects at the National Aeronautic and Space Administration (NASA) is a difficult task. This difficulty is due to the multiple and often conflicting objectives in addition to the inherent technical complexities and valuation uncertainties involved in the assessment process. As such, a systematic and transparent decision support framework is needed to guide the assessment process, shape the decision outcomes and enable confident choices to be made. Methods for solving Multi-Criteria Decision Making (MCDM) problems have been widely used to select a finite number of alternatives generally characterized by multiple conflicting criteria. However, applying these methods is becoming increasingly difficult for technology assessment in the space industry because there are many emerging risks for which information is not available and decisions are made under significant uncertainty. In this paper, we propose a hybrid fuzzy group decision support framework for technology assessment at NASA. The proposed objective framework is comprised of two modules. In the first module, the complicated structure of the assessment criteria and alternatives are represented and evaluated with the Analytic Network Process (ANP). In the second module, the alternative advanced-technology projects are ranked using a customized fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). We demonstrate the applicability of the proposed framework through a case study at the Kennedy Space Center.

1. Introduction

The recent economic crisis and the passage of austere budgets have focused critical attention on government agencies that support technology development. The public is concerned with the governance of these agencies and with obtaining the maximum return on public spending. Public pressure has forced Congress to mandate the National Aeronautic and Space Administration (NASA) to be more accountable in its evaluation of advanced-technology projects. The demand for accountability, the pressure to cut costs and the increasing number of projects has made evaluating advanced-technology projects at NASA extremely difficult (Tavana, 2003).

The technology assessment process at NASA is intended: (1) to identify what technologies are needed and when they need to be available; (2) to develop and implement a rigorous and objective technology prioritization process; and (3) develop technology investment recommendations about which existing projects should continue and which new projects should be established (NASA ESAS Final Report, 2005). The investment recommendations include budget, schedule and program resources needed to develop the advanced technologies required for the exploration architecture, as well as the identification of other investment opportunities to maximize performance and flexibility while minimizing costs and risks. The above visions were developed through a rigorous and objective process consisting of the following: (1) the identification of architecture functional needs; (2) the collection, synthesis, integration, and mapping of technology data; and (3) an objective decision analysis resulting in a detailed technology development investment plan (NASA ESAS Final Report, 2005).

The assessment and selection of projects is an important issue in technology management (Linton, Walsh, & Morabito, 2002; Shehabuddeen, Probert, & Phaal, 2006; Sun & Ma, 2005). The rapid development of technological changes, together with their increasing complexity and variety, has made the task of technology selection a difficult task (Shehabuddeen et al., 2006). The literature on project selection contains hundreds of models, including: scoring methods, ad hoc methods, comparative methods, economic

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http://dx.doi.org/10.1016/j.eswa.2012.07.040

methods, portfolio methods, mathematical optimization methods and simulation methods.

Scoring methods use a relatively small number of quantitative criteria to specify project desirability. In these methods, the merit of each project is determined with respect to each criterion, and then scores are combined to yield an overall performance score for each project (Coldrick, Longhurst, Ivey, & Hannis, 2005; DePiante & Jensen, 1999; Henriksen & Traynor, 1999; Oh, Yang, & Lee, 2012). Ad hoc methods are a special form of scoring methods. In these methods, limits are set for the various criteria levels, and then any projects which fail to meet these limits are eliminated.

Comparative methods consider both quantitative and qualitative criteria. In these methods, the weights of different criteria are determined and alternatives are compared on the basis of their contributions to these criteria, and then a set of project benefit measures is computed. Once the projects have been arranged on a comparative scale, the DMs proceed from the top of the list and select projects until available resources are exhausted (Huang, Chu, & Chiang, 2008; Tiryaki & Ahlatcioglu, 2009).

Economic methods use financial models to calculate the monetary payoff of each project under consideration. Portfolio methods rely on graphical representations of the projects under consideration. In these methods, two dimensions such as the expected monetary value and the likelihood of success are selected, and then a representative mix of projects on the dimensions represented are selected (Eilat, Golany, & Shtub, 2006; Ho & Liao, 2011; Zapata & Reklaitis, 2010).

Mathematical optimization methods try to optimize various objective functions within the constraints of resources, project logic and dynamics, technology, and project-related strategies. They include a wide range of methods, such as linear, non-linear, integer, dynamic, goal and stochastic mathematical programming methods (Beaujon, Marin, & McDonald, 2001; Dickinson, Thornton, & Graves, 2001; Elazouni & Abido, 2011; Kester, Hultink, & Lauche, 2009).

Simulation methods are a special form of decision analysis. In these methods, random numbers are used to generate a large number of problems. Then for each problem, the simulation develops many variables and constraints. DMs then use the model to compare various projects and pick the best outcome. Optimization methods are also a special form of decision analysis. In these methods the DMs select from the list of candidate projects a set that provides maximum benefit (e.g. maximum net present value). These models are generally based on some form of mathematical programming, to support the optimization process and to include project interactions such as resource dependencies and constraints, technical and market interactions, or program considerations (Araúzo, Pajares, & Lopez-Paredes, 2010; Stamelos & Angelis, 2001; Vithayasrichareon & MacGill, 2012).

In this paper, we propose a hybrid fuzzy group decision support framework for advanced-technology assessment and prioritization at NASA. The proposed objective framework is comprised of two modules. In first module, the complicated structure of the prioritization criteria and alternatives are represented with the Analytic Network Process (ANP). This formulation will lead to modeling the dependencies and interdependencies of the attributes and the alternative advanced-technology projects. The uncertainties associated with the qualitative attributes are represented with linguistic terms parameterized through fuzzy sets. A fuzzy goal programming model is supplied to find the fuzzy relative importance weight of the attributes. The interdependencies between the attributes and the dependencies among the sub-attributes are then represented with fuzzy pairwise comparison matrices which in turn are used to calculate the global fuzzy weights of the attributes. We use ANP in the first module because, as suggested by Kengpol and Tuominen (2006), it is able to articulate the decision criteria and it ensures that each of their weights and preferences is internally consistent.

In the second module, the alternative advanced-technology projects are ranked using a customized fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) proposed by Sadi-Nezhad and Khalili-Damghani (2010). The fuzzy relative importance weight of the attributes determined in the first module is used as the inputs in the second module. We use TOPSIS in the second module because it is a well-structured, analytical and objective prioritization method needed for technology assessment at NASA. Shih, Shyur, and Lee (2007) have acknowledged the following four advantages for TOPSIS: (i) a sound logic that represents the rationale of human choice; (ii) a scalar value that accounts for both the best and worst alternatives simultaneously; (iii) a simple computation process that can be easily programmed into a spreadsheet; and (iv) the performance measures of all the alternatives on the attributes can be visualized on a polyhedron, at least for any two dimensions. TOPSIS also has the fewest rank reversals among the common Multi-Attribute Decision Making (MADM) methods (Soltanmohammadi, Osanloo, & Aghajani Bazzazi, 2010).

The remainder of the paper is organized as follows. In Section 2, we review the relevant MADM literature. In Section 3, we present the hybrid fuzzy group decision support framework proposed in this study. In Section 4, we demonstrate the applicability of the proposed framework through a case study conducted at the Kennedy Space Center to assess and prioritize advanced-technology projects. In Section 5, we present our conclusions and future research directions.

2. Literature review

The Multi-Criteria Decision Making (MCDM) methods are frequently used to solve real-world problems with multiple, conflicting and incommensurate criteria. MCDM problems are generally categorized as continuous or discrete, depending on the domain of alternatives. Hwang and Yoon (1981) have classified the MCDM methods into two categories: Multi-Objective Decision Making (MODM) and MADM. MODM has been widely studied by means of mathematical programming methods with well-formulated theoretical frameworks (Sakawa, 1993). MODM methods have decision variable values that are determined in a continuous or integer domain with an infinite or a large number of alternative choices, the best of which should satisfy the Decision Maker's (DM's) constraints and preference priorities (Ehrgott & Wiecek, 2005; Hwang & Masud, 1979). MADM methods, on the other hand, have been used to solve problems with discrete decision spaces and a predetermined or a limited number of alternative choices. The MADM solution process requires inter and intra-attribute comparisons and involves implicit or explicit tradeoffs (Hwang & Yoon, 1981).

Fuzzy MADM methods have been developed due to the lack of precision in assessing the relative importance weight of the attributes and the performance ratings of the alternatives in real-world problems. This imprecision may come from a variety of sources such as: (1) unquantifiable information; (2) incomplete information; (3) non-obtainable information; and/or (4) partial ignorance (Chen, Hwang, & Hwang, 1992). The classic MADM methods cannot effectively handle problems with imprecise or vague information (Chen et al., 1992). When Bellman and Zadeh (1970), and a few years later Zimmermann (1985), introduced fuzzy sets into the field, they cleared the way for a new family of methods to deal with problems which had been inaccessible to and unsolvable with standard MCDM techniques.

In fuzzy MCDM, the imprecision and vagueness associated with the qualitative data can be represented more logically with linguistic variables and overlapping membership functions. In addition, the data which are measured in different units can be used directly without standardization. A major advantage of fuzzy logic is that it can be used as compensatory and non-compensatory in a single model in different contexts, by using inferences through judgments provided by the DM. The distinction between the compensatory and non-compensatory evaluation is that the former takes into consideration the trade-offs between the evaluation criteria, while the latter ignores the value trade-offs (Keeney, 1980).

2.1. AHP and fuzzy AHP

The Analytical Hierarchical Process (AHP) is a well-known MADM approach proposed by Saaty (1977, 1980) to simplify complex and ill-structured problems by arranging the decision attributes and alternatives in a hierarchical structure with the help of a series of pairwise comparisons. Dyer and Forman (1992) describe the advantages of AHP in a group setting as follows: (1) the discussion focuses on both tangibles and intangibles, individual and shared values; (2) the discussion can be focused on objectives rather than alternatives; (3) the discussion can be structured so that every attribute can be considered in turn; and (4) the discussion continues until all relevant information has been considered and a consensus choice of the decision alternatives is achieved.

Saaty (2005) argues that a DM naturally finds it easier to compare two things than to compare all things together in a list. AHP also examines the consistency of the DMs and allows for the revision of their responses. AHP has been applied to many diverse decisions because of the intuitive nature of the process and its power in resolving the complexities in judgmental problems. A comprehensive list of the major applications of AHP can be found in Omkarprasad and Sushil (2006) and Seyhan and Mehpare (2010).

In spite of its widespread use and popularity, the conventional AHP method is not capable of handling the uncertainty and vagueness involved in mapping the DMs' qualitative preferences to point estimates in the pairwise comparison matrices. The problem of generating a priority vector from an uncertain pairwise comparison matrix is the basis for the fuzzy AHP concept. There are the several procedures for generating priority vectors in fuzzy AHP problems. The geometric mean method (Buckley, 1985), fuzzy logarithmic least square method (Boender, de Graan, & Lootsma, 1989), synthetic extend analysis (Chang, 1996), fuzzy least square method (Xu, 2000), direct fuzzification method (Buckley, Feuring, & Hayashi, 2001; Csutora & Buckley, 2001), fuzzy preference programming (Mikhailov, 2003) and two-stage logarithmic programming (Wang, Yang, & Xu, 2005) are some of these methods.

Recent applications of the fuzzy AHP are, amongst others, performance evaluation of bus companies (Yeh & Yo-Hern, 2000); information technology assessment (Mikhailov & Tsvetinov, 2004); new product development decisions (Büyüközkam & Feyzioglu, 2004); managerial talent assessment (Huang & Wu, 2005); evaluation of critical success factors in e-commerce (Kong & Liu, 2005); assessment of water management plans (Sredjevic & Medeiros, 2008); research and development project assessment (Huang et al., 2008); safety management evaluation (Dağdeviren & Yüksel, 2008); evaluation of critical success factors in knowledge sharing (Lin, Lee, & Wang, 2009); evaluation of enterprise resource planning systems (Cebeci, 2009); selection of human resources (Güngör, Serhadlioğlu, & Kesen, 2009); weapon selection (Dağdeviren, Yavuz, & Kilinç, 2009); evaluation of operators with multiple skills (Şen & Çinar, 2010); analysis of healthcare service quality (Büyüközkan, Çifçi, & Güleryüz, 2011); selection of wafer fabrication process (Rajput, Milani, & Labun, 2011) and risk assessment (Wang, Chan, Yee, & Diaz-Rainey, 2012).

2.2. ANP and fuzzy ANP

The Analytic Network Process (ANP), also introduced by Saaty (1996), is a generalization of the AHP. AHP models are represented with unidirectional hierarchical relationships. However, ANP models allow for complex inter-relationships among the decision levels and the attributes. The feedback mechanism in AHP replaces the hierarchical structure with a network structure where the relationships between levels are not simply represented as higher or lower, dominant or subordinate, direct or indirect (Meade & Sarkis, 1999). In other words, while the importance of the criteria determines the importance of the alternatives in a hierarchy, the importance of the alternatives may also have impact on the importance of the criteria. AHP solves the problem of independence among the alternatives or criteria and ANP solves the problem of dependence among the alternatives or criteria by obtaining the composite weights through the development of a "supermatrix" (Shyur, 2006). The supermatrix is actually a partitioned matrix, where each matrix segment represents a relationship between two components or clusters in a system (Saaty, 2005).

The inability of ANP to deal with the imprecise or uncertain judgments has been improved in fuzzy ANP. Instead of a crisp value, fuzzy ANP applies a range of values to incorporate the DM's imprecise or uncertain judgments in the pairwise comparison process. Recent applications of the fuzzy ANP are, transportation-mode selection (Tuzkaya & Önüt, 2008); faulty behavior risk assessment in work systems (Dağdeviren, Yüksel, & Kurt, 2008); shipyard location selection (Guneri, Cengiz, & Seker, 2009); evaluation of high-speed public transportation (Gumus & Yilmaz, 2010); selecting container ports (Onut, Tuzkaya, & Torun, 2011); agricultural drought risk assessment (Chen & Yang, 2011); evaluation of airline industry (Sevkli et al., 2012); professional selection (Kabak, Burmaoğlu, & Kazançoğlu, 2012) and strategy prioritization (Babaesmailli, Arbabshirani, & Golmah, 2012), amongst others.

2.3. TOPSIS and fuzzy TOPSIS

TOPSIS was initially proposed by Hwang and Yoon (1981). According to this technique, the best alternative is the one that is nearest to the ideal solution and farthest from the nadir (negative ideal) solution (Ertugrul & Karakasoglu, 2007). The ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas, the nadir solution is a solution that maximizes the cost criteria and minimizes the benefit criteria (Wang & Elhag, 2006). In other words, the ideal solution is comprised of all the best values attainable from the criteria, whereas, the nadir solution is comprised of all the worst values attainable from the criteria (Wang, 2008).

TOPSIS has been shown to be one of the best MADM methods in addressing the rank reversal issue, which is the change in the ranking of alternatives when a non-optimal alternative is introduced (Zanakis, Solomon, Wishart, & Dublish, 1998). This consistency feature is largely appreciated in practical applications. Moreover, the rank reversal in TOPSIS is insensitive to the number of alternatives and has its worst performance only in the case of a very limited number of attributes (Triantaphyllou & Lin, 1996; Zanakis et al., 1998). A relative advantage of TOPSIS is its ability to identify the best alternative quickly (Paxkan & Wu, 1997).

Despite its popularity and simplicity in concept, the conventional TOPSIS is often criticized because of its inability to deal with uncertainty and imprecision inherent in the real-world problems. In the conventional formulation of TOPSIS, the DMs' judgments are represented by precise numerical values. However, often in practical cases the DMs might not be able to assign numerical values to their judgments. Fuzzy TOPSIS has been widely applied to solve various multi-attribute problems.

Recent applications of the fuzzy TOPSIS include: bridge risk assessment (Wang & Elhag, 2006); total quality management consultant selection (Saremi, Mousavi, & Sanayei, 2009); assessing thermal-energy storage in concentrated solar power systems (Cavallaro, 2010); oil spill accidents in the sea (Krohling & Campanharo, 2011); analyzing business competition in the airline industry (Torlak, Sevkli, Sanal, & Zaim, 2011); evaluating sustainable transportation systems (Awasthi, Chauhan, & Omrani, 2011); energy planning (Kaya & Kahraman, 2011); product adoption decisions (Kim, Lee, Cho, & Kim, 2011); manager selection (Kelemenis, Ergazakis, & Askounis, 2011); evaluating business intelligence for enterprise systems (Rouhani, Ghazanfari, & Jafari, 2012); bank location planning (İç, 2012); wireless network selection (Chamodrakas & Martakos, 2012) and facility location planning (Mokhtarian & Hadi-Vencheh, 2012).

3. Proposed fuzzy group decision support framework

The fuzzy group decision support framework proposed in this study is comprised of two distinct modules. The first module is designed to derive the fuzzy relative importance weights of the attributes in the multi-attribute project selection problem using a fuzzy ANP method. The second module is designed to rank the alternatives using a fuzzy TOPSIS method. The relative importance weight of the attributes and the performance score of the alternatives are assumed to be triangular fuzzy numbers (TFNs).

3.1. Fuzzy ANP method

In this module we use fuzzy ANP to capture the DMs' judgments and determine the fuzzy weight of the attributes through a series of fuzzy pairwise comparisons. Consider the following fuzzy pairwise comparison matrix with n elements for the kth DM:

$$\widetilde{A}^k = \begin{bmatrix} 1 & \tilde{a}_{12}^k & \cdots & \tilde{a}_{1n}^k \\ \tilde{a}_{21}^k & 1 & \cdots & \tilde{a}_{2n}^k \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{a}_{n1}^k & \tilde{a}_{n2}^k & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & (l_{12}, m_{12}, u_{12})_k & \cdots & (l_{1n}, m_{1n}, u_{1n})_k \\ (l_{21}, m_{21}, u_{21})_k & 1 & \cdots & (l_{2n}, m_{2n}, u_{2n})_k \\ \vdots & \vdots & \cdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1})_k & (l_{n2}, m_{n2}, u_{n2})_k & \cdots & 1 \end{bmatrix}, \quad k = 1, 2, 3, \ldots, m \tag{1}$$

where, $\tilde{a}_{ij}^k = (l_{ij}, m_{ij}, u_{ij})_k$ is a TFN for the preference of attribute i over attribute j for the kth DM. We should note that the DM only provides $n(n-1)/2$ pairwise comparisons and the reciprocal properties are used to fill-in the second half of the pairwise comparison matrix (i.e., $\tilde{a}_{ij} = 1/\tilde{a}_{ji}, \forall i, j$). The theoretical fuzzy pairwise comparison matrix can be expressed as follows:

$$\widetilde{W} = \begin{bmatrix} 1 & \frac{\tilde{w}_1}{\tilde{w}_2} & \cdots & \frac{\tilde{w}_1}{\tilde{w}_n} \\ \frac{\tilde{w}_2}{\tilde{w}_1} & 1 & \cdots & \frac{\tilde{w}_2}{\tilde{w}_n} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\tilde{w}_n}{\tilde{w}_1} & \frac{\tilde{w}_n}{\tilde{w}_2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \frac{(w_l, w_m, w_u)_1}{(w_l, w_m, w_u)_2} & \cdots & \frac{(w_l, w_m, w_u)_1}{(w_l, w_m, w_u)_n} \\ \frac{(w_l, w_m, w_u)_2}{(w_l, w_m, w_u)_1} & 1 & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{(w_l, w_m, w_u)_n}{(w_l, w_m, w_u)_1} & \frac{(w_l, w_m, w_u)_n}{(w_l, w_m, w_u)_2} & \cdots & 1 \end{bmatrix} \tag{2}$$

We then calculate a fuzzy relative importance weight vector, $\widetilde{W} = (\widetilde{W}_1, \widetilde{W}_2, \ldots, \widetilde{W}_n) = ((w_l, w_m, w_u)_1, (w_l, w_m, w_u)_2, \ldots, (w_l, w_m, w_u)_n)$, such that its total deviation from the fuzzy pairwise comparison matrices of the DMs is minimized. The following multi-objective fuzzy mathematical programming model is proposed for this purpose:

$$\begin{aligned} Min \ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}\left|\tilde{w}_i - \tilde{a}_{ij}^k \otimes \tilde{w}_j\right|, \quad k = 1, 2, \ldots, m \\ s.t. \ & \sum_{j=1}^{n}\tilde{w}_j \cong 1, \\ & \tilde{w}_j \geqslant 0, \quad j = 1, 2, \ldots, n \end{aligned} \tag{3}$$

Next, we replace the TFNs in (3) and construct the following fuzzy multi-objective mathematical programming model:

$$\begin{aligned} Min \ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}\left|(w_l)_i - l_{ij}^k \times (w_l)_j\right|, \quad k = 1, 2, \ldots, m \\ Min \ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}\left|(w_m)_i - m_{ij}^k \times (w_m)_j\right|, \quad k = 1, 2, \ldots, m \\ Min \ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}\left|(w_u)_i - u_{ij}^k \times (w_u)_{ij}\right|, \quad k = 1, 2, \ldots, m \\ s.t. \ & \sum_{j=1}^{n}(w_m)_j \cong 1, \\ & (w_m)_j - (w_l)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_u)_j - (w_m)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_l)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_m)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_u)_j \geqslant 0, \quad j = 1, 2, \ldots, n \end{aligned} \tag{4}$$

The derived weight vector in (4) may not fully satisfy all the DMs. Therefore, we propose the following goal programming model to minimize the gap between the derived weight vector and the DMs' judgments:

$$\begin{aligned} Min \ & \theta = \sum_{k=1}^{m}\alpha_k\left(d_{lk}^+ + d_{mk}^+ + d_{uk}^+\right) + \beta_k\left(d_{lk}^- + d_{mk}^- + d_{uk}^-\right) \\ s.t. \ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}((w_l)_i - l_{ij}^k \times (w_l)_j) - d_{lk}^+ + d_{lk}^- = 0, \quad k = 1, 2, \ldots, m \\ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}((w_m)_i - m_{ij}^k \times (w_m)_j) - d_{mk}^+ + d_{mk}^- = 0, \quad k = 1, 2, \ldots, m \\ & \sum_{i=1}^{n-1}\sum_{j=2}^{n}((w_u)_i - u_{ij}^k \times (w_u)_j) - d_{uk}^+ + d_{uk}^- = 0, \quad k = 1, 2, \ldots, m \\ & \sum_{j=1}^{n}(w_m)_j \cong 1, \\ & (w_m)_j - (w_l)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_u)_j - (w_m)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_l)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_m)_j \geqslant 0, \quad j = 1, 2, \ldots, n \\ & (w_u)_j \geqslant 0, \quad j = 1, 2, \ldots, n \end{aligned} \tag{5}$$

where, α_k and β_k are the relative importance weight of the kth DM's opinions. Solving (5) will result in a fuzzy weight vector where it's total deviation from the collective opinions of k different DMs is minimized.

We use the aforementioned procedure in the fuzzy ANP approach proposed by Dağdeviren and Yüksel (2010) to calculate the importance weight of the attributes and sub-attributes:

Step 1. Identify all the relevant attributes and sub-attributes involved in the group project selection problem.

Step 2. Construct a network structure for the goal, attributes and sub-attributes.

Step 3. Advise DMs to assume no dependency among the attributes and sub-attributes (simply consider a hierarchical structure) and develop their fuzzy comparison judgments using the linguistic terms associated with the TFNs.

Step 4. Determine the local fuzzy weight of the attributes and sub-attributes using the fuzzy goal programming model (5).

Step 5. Determine an inner fuzzy dependence matrix with a fuzzy scale for each attribute with respect to the other attributes. This inner dependence matrix is multiplied with the local fuzzy weights of the attributes, determined in Step 4, to compute the interdependent fuzzy weight of the attributes.

Step 6. Calculate the global fuzzy weights for the sub-attributes. The global sub-attribute weights are computed by multiplying the local weight of the sub-attributes into the interdependent weight of its higher-level attribute.

3.2. Fuzzy TOPSIS method

Several variations of the fuzzy TOPSIS method have been proposed in the literature. The main differences between these methods are in (1) the normalization method used in the decision matrix; (2) the procedure used to identify the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS); and (3) the method used to calculate the distance between the fuzzy numbers.

We use a modified fuzzy TOPSIS approach based on the Preference Ratio (PR) method proposed by Modarres and Sadi-Nezhad (2001) and the fuzzy distance measurement proposed by Sadi-Nezhad and Khalili-Damghani (2010, 2011). The PR method is employed to determine the preference of the fuzzy numbers relative to an interval rather than in absolute terms and the fuzzy distance measurement is utilized because it is more realistic that the distances between a set of fuzzy numbers be a fuzzy measure rather than a precise measure. Sadi-Nezhad and Khalili-Damghani (2010, 2011) used an efficient version of the fuzzy distance measurement proposed by Chakraborty and Chakraborty (2007) and Guha and Chakraborty (2010) in their TOPSIS procedure. As the details of the efficient fuzzy distance measurement can be found in Sadi-Nezhad and Khalili-Damghani (2010, 2011), a brief introduction is provided here.

Assume that k DMs are considering a MADM problem with m alternatives and n attributes. Let $\tilde{x}_{ij}^k$ be the score assigned to the ith alternative with respect to jth attribute by the kth DM. Assuming that the weights of the attributes are determined according to the fuzzy ANP module described in the previous section as fuzzy numbers, the problem can be represented formally as follows:

$$\widetilde{D}^k = \begin{bmatrix} \tilde{x}_{11}^k & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1j}^k \\ \tilde{x}_{21}^k & \tilde{x}_{22}^k & \cdots & \tilde{x}_{2j}^k \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{i1}^k & \tilde{x}_{i2}^k & \cdots & \tilde{x}_{ij}^k \end{bmatrix}, \quad \widetilde{W} = [\,\tilde{w}_1 \quad \tilde{w}_2 \quad \cdots \quad \tilde{w}_j\,] \tag{6}$$

$\widetilde{D}^k$ is the fuzzy decision matrix for the kth DM with i rows and j columns representing the alternatives and the attributes, respectively. The fuzzy weight of the attributes is represented by the $\widetilde{W}$ vector derived through Model (5). The k decision matrices can be aggregated as follows:

$$\widetilde{D} = \begin{bmatrix} \tilde{n}_{11} & \tilde{n}_{12} & \cdots & \tilde{n}_{1j} \\ \tilde{n}_{21} & \tilde{n}_{22} & \cdots & \tilde{n}_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{n}_{i1} & \tilde{n}_{i2} & \cdots & \tilde{n}_{ij} \end{bmatrix} \quad \text{where } \tilde{n}_{ij} = \frac{\tilde{n}_{ij}^1 + \tilde{n}_{ij}^2 + \cdots + \tilde{n}_{ij}^k}{k} \tag{7}$$

Assuming that all data are TFNs, the second module can be described through the following steps:

Step 1. Apply a columnar normalization for smoothing the decision matrices and representing them with matrix $\widetilde{N}$ as follows:

$$\widetilde{N} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1j} \\ \tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2j} \\ M & M & M & M \\ \tilde{r}_{i1} & \tilde{r}_{i2} & \cdots & \tilde{r}_{ij} \end{bmatrix} \quad \text{where}$$

$$\tilde{r}_{ij} = \begin{cases} \left(\frac{l_{ij}}{d_j^+}, \frac{m_{ij}}{d_j^+}, \frac{u_{ij}}{d_j^+}\right) & \text{if } j \text{ is a benefit attribute} \\ \left(\frac{l_{ij}^-}{u_{ij}}, \frac{l_{ij}^-}{m_{ij}}, \frac{l_{ij}^-}{l_{ij}}\right) & \text{if } j \text{ is a cost attributeand } u_j^+ \text{ is not zero} \\ \left(1-\frac{l_{ij}}{u_j^+}, 1-\frac{m_{ij}}{u_j^+}, 1-\frac{u_{ij}}{u_j^+}\right) & \text{if } j \text{ is a cost attributeand } u_j^+ \text{ is zero} \end{cases} \tag{8}$$

$$u_j^+ = \max(u_{ij}), \quad a_{ij}^- = \min(l_{ij}), \qquad i = 1,2,\ldots,m. \tag{9}$$

Step 2. Construct the weighted normalized decision matrix using the global weights of the attributes from the proposed fuzzy ANP module described earlier as follows:

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1j} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{v}_{i1} & \tilde{v}_{i2} & \cdots & \tilde{v}_{ij} \end{bmatrix}, \quad \tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j, \tag{10}$$
$$i = 1,2,\ldots,n; \; j = 1,2,\ldots,m.$$

where, $\tilde{v}_{ij}$ is a normalized TFN and varies in a closed interval $[0, 1]$.

Step 3. Define the FPIS and the FNIS as follows and represent them with S^+ and S^-, respectively:

$$S^+ = (\,\tilde{v}_{i1}^+ \quad \tilde{v}_{i2}^+ \quad \cdots \quad \tilde{v}_{ij}^+\,)$$

where,

$$\begin{aligned} &\tilde{v}_{ij}^+ = \max v_{ij} = (\max l_{ij}, \max m_{ij}, \max u_{ij}), \\ &i = 1,2,\ldots,n \text{ if } j \text{ is a benefit attribute}, \\ &\tilde{v}_{ij}^+ = \min v_{ij} = (\min l_{ij}, \min m_{ij}, \min u_{ij}), \\ &i = 1,2,\ldots,n \text{ if } j \text{ is a cost attribute}. \end{aligned} \tag{11}$$

$$S^- = (\,\tilde{v}_{i1}^- \quad \tilde{v}_{i2}^- \quad \cdots \quad \tilde{v}_{ij}^-\,)$$

Table 1
Advanced-technology projects under consideration.

Project	Cost ($)
Hubble	1,778,000
Photo-Voltaic	1,908,000
Airlock	1,515,000
Babaloon	1,949,000
Planet-Finder	1,266,000
Nebula	1,348,000
Solar	1,176,000
Truss	1,347,000
Centrifuge	1,790,000
Tether	961,000
Total	15,038,000

Table 2
DM groups and their assessment attributes.

Attribute	Sub-attribute	Abbreviation
Safety	Eliminating the possibility of death or serious injury	ST-DSI
	Eliminating the possibility of loss of flight hardware, facility, or GSE	ST-LOF
	Eliminating the possibility of personal injury and/or flight hardware, facility, or GSE damage	ST-PID
	Eliminating the possibility of a serious violation of safety, health, or environmental federal/state regulation	ST-SVS
	Eliminating the possibility of a dimness violation of safety, health, or environmental federal/state regulation	ST-DVS
Systems Engineering	Reducing the probability of launch slippage	ET-LSP
	Supporting program for near-term requirements	ET-NTR
	Eliminating occurrence of non-support activities	ET-NON
	Fixing a failure	ET-FIX
	Eliminating reliance on identified obsolete technology	ET-TCH
Program Office	Meeting safety/launch & landing criteria	PT-PRI
	Availability of funds	PT-FUN
	Utilizing time-sensitive implementation methodology	PT-IMP
	Meeting the proposed cost	PT-CST
	Meeting the proposed schedule	PT-SCH
	Reducing O&M costs	PT-OMC
	Meeting contractual obligations	PT-CON
Operations	Using less people	OT-PEP
	Reducing time	OT-TIM
	Ability to access the work location	OT-LOC
	Reducing/eliminating hardware/materials expended during processing	OT-HNM
Reliability	Eliminating critical single failure points (CSFPs)	RT-SFP
	Reducing the possibility of failure propagation to other components or systems	RT-PFP
	Improving mean time to repair (MTTR)	RT-MTR
	Improving identification/fault isolation (FI/FI)	RT-FII
	Providing for a simpler system	RT-SIM
	Improving access for maintenance tasks	RT-AMT
	Increasing mean time between failures (MTBFs)	RT-TBF
	Reducing support equipment, special tools, and special training requirements	RT-ETT
	Providing for the use of standard commercial of-the-shelf (COTS) parts	RT-COT
	Providing for equipment interchangeability	RT-EQI
Implementation	Reducing/eliminating multi-site applicability	IT-MSA
	Reducing/eliminating possibility of interference in implementation (window of opportunity)	IT-WOO
	Reducing/eliminating possibility of flight manifest changes	IT-FMC
	Reducing/eliminating effects on multi-system configuration systems	IT-MSC
	Reducing/eliminating possibility of equipment and occupational hazards	IT-EOH
	Reducing/eliminating site specific restrictions	IT-SSR
	Ability to meet new technology considerations	IT-TCH

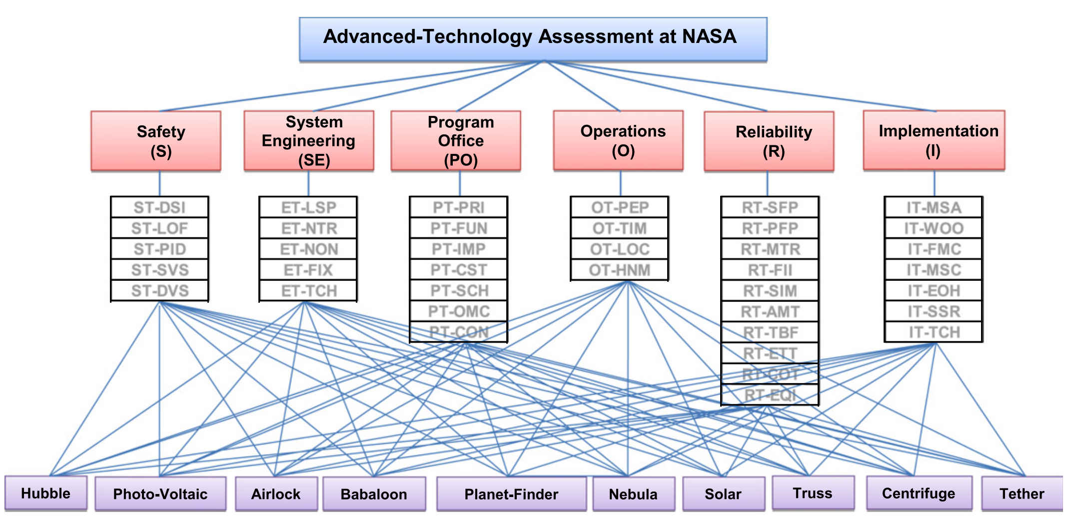

Fig. 1. Hierarchical structure of the advanced-technology project assessment at NASA.

where,

$$\begin{aligned} &\tilde{v}_{ij}^{-} = \min v_{ij} = (\min l_{ij}, \min m_{ij}, \min u_{ij}),\\ &i = 1,2,\ldots,n \text{ if } j \text{ is a benefit attribute},\\ &\tilde{v}_{ij}^{-} = \max v_{ij} = (\max l_{ij}, \max m_{ij}, \max u_{ij}),\\ &i = 1,2,\ldots,n \text{ if } j \text{ is a cost attribute}. \end{aligned} \tag{12}$$

Step 4. Calculate the fuzzy distance of each alternative from S^+ and S^-. Denote these distances as the Positive Fuzzy Distance (PFD) and the Negative Fuzzy Distance (NFD), respectively:

$$P\widetilde{F}D_i = \tilde{d}(A_i, S^+), \quad i = 1,2,\ldots,n \tag{13}$$

$$N\widetilde{F}D_i = \tilde{d}(A_i, S^-), \quad i = 1,2,\ldots,n \tag{14}$$

Table 3
Linguistic variables and TFNs used for the relative importance weight of the attributes and sub-attributes.

Linguistic variable	TFN scale	TFN reciprocal scale
Just equal (JE)	(1, 1, 1)	(1, 1, 1)
Equally important (EI)	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important (VMI)	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important (SMI)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important (VSMI)	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more important (AMI)	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

Table 4
Local weight of the selection attributes and sub-attributes.

Attribute (local weight)	Sub-attribute	Local weights
S (0.36, 0.38, 0.53)	ST-DSI	(0.18, 0.564, 0.95)
	ST-LOF	(0.17, 0.239, 0.28)
	ST-PID	(0.02, 0.118, 0.22)
	ST-SVS	(0.03, 0.047, 0.07)
	ST-DVS	(0.03, 0.032, 0.06)
E (0.03, 0.13, 0.14)	ET-LSP	(0.2, 0.553, 1.07)
	ET-NTR	(0.08, 0.171, 0.33)
	ET-NON	(0.01, 0.132, 0.2)
	ET-FIX	(0.03, 0.107, 0.19)
	ET-TCH	(0.02, 0.037, 0.04)
P (0.03, 0.09, 0.11)	PT-PRI	(0.19, 0.391, 0.51)
	PT-FUN	(0.05, 0.197, 0.21)
	PT-IMP	(0.11, 0.147, 0.27)
	PT-CST	(0.08, 0.105, 0.17)
	PT-SCH	(0.08, 0.086, 0.09)
	PT-OMC	(0, 0.045, 0.06)
	PT-CON	(0.01, 0.029, 0.06)
O (0.01, 0.06, 0.11)	OT-PEP	(0.56, 0.563, 1.04)
	OT-TIM	(0.11, 0.246, 0.46)
	OT-LOC	(0.1, 0.124, 0.23)
	OT-HNM	(0.05, 0.067, 0.08)
R (0.06, 0.28, 0.45)	RT-SFP	(0.3, 0.412, 0.81)
	RT-PFP	(0.12, 0.194, 0.19)
	RT-MTR	(0.08, 0.11, 0.19)
	RT-FII	(0.06, 0.092, 0.13)
	RT-SIM	(0.01, 0.053, 0.06)
	RT-AMT	(0.03, 0.049, 0.09)
	RT-TBF	(0.01, 0.04, 0.07)
	RT-ETT	(0.01, 0.03, 0.06)
	RT-COT	(0.01, 0.01, 0.01)
	RT-EQI	(0.01, 0.01, 0.01)
I (0.04, 0.06, 0.07)	IT-MSA	(0.21, 0.423, 0.82)
	IT-WOO	(0.06, 0.195, 0.25)
	IT-FMC	(0.07, 0.137, 0.24)
	IT-MSC	(0.02, 0.116, 0.23)
	IT-EOH	(0.05, 0.065, 0.12)
	IT-SSR	(0.03, 0.033, 0.06)
	IT-TCH	(0.03, 0.031, 0.06)

The details of the fuzzy distance measurement can be found in Sadi-Nezhad and Khalili-Damghani (2010, 2011).

Step 5. Define a fuzzy closeness coefficient (FCC) as follows:

$$\widetilde{FCC}_i = \frac{\tilde{d}(A_i, S^-)}{\tilde{d}(A_i, S^-) + \tilde{d}(A_i, S^+)} = \frac{\widetilde{NFD}_i}{\widetilde{NFD}_i + \widetilde{PFD}_i} \quad i = 1, 2, \ldots, n \tag{15}$$

When the $\widetilde{FCC}_i$, $i = 1, 2, \ldots, n$ value is close to unit, the utility of the associated alternative is higher for the group of DMs. However, the $\widetilde{FCC}_i$, $i = 1, 2, \ldots, m$ are TFNs and are compared relative to a proposed interval using PR.

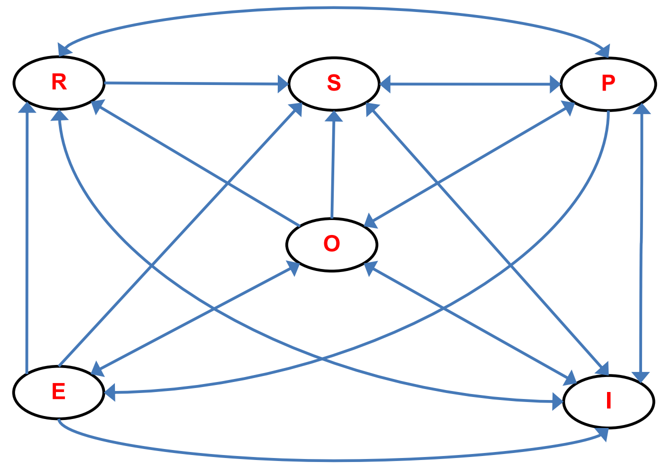

Fig. 2. Interdependencies among the assessment attributes.

Table 5
Dependencies and interdependencies among the attributes.

Attribute	S	E	P	O	R	I
Safety (S)	–	–	+	–	–	+
System Engineering (E)	+	–	–	+	+	+
Program Office (P)	+	+	–	+	+	+
Operations (O)	+	+	+	–	+	+
Reliability (R)	+	–	+	–	–	+
Implementation (I)	+	–	+	+	+	–

Step 6. Order the fuzzy $\widetilde{FCC}_i$, $i = 1, 2, \ldots, n$ in a non-increasing mode based on the PR measurement and choose the alternative with the largest FCC.

4. Case study: assessment of advanced-technology projects at NASA[2]

The project engineering office at the Kennedy Space Center (KSC) currently uses the Consensus Ranking Organizational Support System (CROSS) proposed by Tavana (2003) to assess advanced-technology projects initiated by the contractors or divisions within the KSC. Project evaluation is the primary responsibility of the Ground System Working Team (GSWT), which currently has six members representing the six divisions of Safety (S), System Engineering (E), Program Office (P), Operations (O), Reliability (R) and Implementation (I). The contractors and divisions within the KSC submit approximately 30 to 50 proposals for evaluation and possible funding annually. The GSWT uses CROSS to assess the importance of each project relative to the longevity of the space program and select the most suitable projects for funding depending on the available budget for that fiscal year. One of the shortfalls of CROSS is its ability to handle imprecise or vague data. Imprecise or vague data may be the result of unquantifiable, incomplete and non-obtainable information. Imprecise or vague data is often expressed with bounded intervals, ordinal (rank order) data or fuzzy numbers. We use fuzzy numbers and the procedure proposed in this study to deal with situations where some of the data are imprecise or vague.

The six members of the GSWT (hereafter referred to as "Decision Makers" or "DMs") have been commissioned to assess the following 10 projects given in Table 1 along with their proposed

[2] All the names and data in the case study are changed to protect the anonymity of the projects.

Table 6
Linguistic variables and TFNs used for the dependencies and the interdependencies among the attributes.

Linguistic variable	TFN scale
No effect (NE)	(0, 0, 0)
Very weak effect (VWE)	(0, 0.2, 0.4)
Weak effect (WE)	(0.2, 0.4, 0.6)
Medium effect (ME)	(0.4, 0.6, 0.8)
High effect (HE)	(0.6, 0.8, 1)
Very high effect (VHE)	(1, 1, 1)

budget for possible funding: Hubble, Photo-Voltaic, Airlock, Babaloon, Planet-Finder, Nebula, Solar Truss, Centrifuge and Tether.

As shown in Table 1, the total cost of funding all 10 projects is \$15,038,000. However, the available budget is \$6 million. The six divisions of Safety, System Engineering, Program Office, Operations, Reliability and Implementation were designated as the primary attributes for advanced-technology project assessment at KSC. Initially, the DMs identified a set of sub-attributes within each attribute for evaluating the projects. Table 2 presents the attributes and sub-attributers used in this study. A hierarchical structure of the overall goal, the attributes, the sub-attribute's and the projects considered in this study is depicted in Fig. 1.

Each DM then used the linguistic variables provided in Table 3 to represent his or her fuzzy comparison matrices of the attributes and sub-attributes. The TFN scale and the TFN reciprocal scale used to represent the linguistic variables with fuzzy numbers were proposed by Kahraman, Ertay, and Büyüközkan (2006) and subsequently used by several authors to solve fuzzy decision-making problems (Dağdeviren & Yüksel, 2010; Tolga, Demircan, & Kahraman, 2005).

The DMs performed a pairwise comparison of the attributes and the sub-attributes by considering the hierarchical structure given in Fig. 1 (regardless of any potential interdependency among them) and the linguistic variables and the TFNs given in Table 3. The local fuzzy weights of the attributes and sub-attributes presented in Table 4 were computed using the proposed mathematical programming model (5).

The DMs then collectively identified the interdependencies among the selection attributes. Fig. 2 shows a graphical representation of these interdependencies and Table 5 shows a tabular representation of these interdependencies. For example, Safety influences Program Office and Implementation while Safety is influenced by Systems Engineering, Program Office, Operations, Reliability and Implementation. For a pair of attributes *a* and *b*, if *a* influences *b* but *b* does not influence *a*, there is a *dependency* between *a* and *b*. However, if *a* influences *b* and *b* influences *a*, there is an *interdependency* between *a* and *b*. For example, Safety and Operations are *dependent* because Operations influences Safety but Safety does not influence Operations. However, Safety and Program Office are *interdependent* because Safety influences Program Office and Program Office influences Safety.

Next, the linguistic variables and the TFNs presented in Table 6 were used with the proposed mathematical programming model (5) to calculate the relative importance of the dependencies and interdependencies among the attributes given in Table 7 using all

Table 8
Calculated global weights of the selection sub-attributes.

Attribute (interdependent weight)	Sub-attribute	Global weights
S (0.096, 0.132, 0.24)	ST-DSI	(0.009, 0.21432, 0.5605)
	ST-LOF	(0.0085, 0.09082, 0.1652)
	ST-PID	(0.001, 0.04484, 0.1298)
	ST-SVS	(0.0015, 0.01786, 0.0413)
	ST-DVS	(0.0015, 0.01216, 0.0354)
E (0.13, 0.372, 0.83)	ET-LSP	(0.01, 0.07189, 0.2461)
	ET-NTR	(0.004, 0.02223, 0.0759)
	ET-NON	(0.0005, 0.01716, 0.046)
	ET-FIX	(0.0015, 0.01391, 0.0437)
	ET-TCH	(0.001, 0.00481, 0.0092)
P (0.194, 0.506, 1.04)	PT-PRI	(0.0038, 0.03519, 0.0816)
	PT-FUN	(0.001, 0.01773, 0.0336)
	PT-IMP	(0.0022, 0.01323, 0.0432)
	PT-CST	(0.0016, 0.00945, 0.0272)
	PT-SCH	(0.0016, 0.00774, 0.0144)
	PT-OMC	(0, 0.00405, 0.0096)
	PT-CON	(0.0002, 0.00261, 0.0096)
O (0.072, 0.34, 0.848)	OT-PEP	(0.028, 0.03378, 0.1144)
	OT-TIM	(0.0055, 0.01476, 0.0506)
	OT-LOC	(0.005, 0.00744, 0.0253)
	OT-HNM	(0.0025, 0.00402, 0.0088)
R (0.048, 0.084, 0.176)	RT-SFP	(0.033, 0.11536, 0.4131)
	RT-PFP	(0.0132, 0.05432, 0.0969)
	RT-MTR	(0.0088, 0.0308, 0.0969)
	RT-FII	(0.0066, 0.02576, 0.0663)
	RT-SIM	(0.0011, 0.01484, 0.0306)
	RT-AMT	(0.0033, 0.01372, 0.0459)
	RT-TBF	(0.0011, 0.0112, 0.0357)
	RT-ETT	(0.0011, 0.0084, 0.0306)
	RT-COT	(0.0011, 0.0028, 0.0051)
	RT-EQI	(0.0011, 0.0028, 0.0051)
I (0.048, 0.242, 0.646)	IT-MSA	(0.0105, 0.02538, 0.082)
	IT-WOO	(0.003, 0.0117, 0.025)
	IT-FMC	(0.0035, 0.00822, 0.024)
	IT-MSC	(0.001, 0.00696, 0.023)
	IT-EOH	(0.0025, 0.0039, 0.012)
	IT-SSR	(0.0015, 0.00198, 0.006)
	IT-TCH	(0.0015, 0.00186, 0.006)

Table 9
Linguistic variables and TFNs used for the rating of the projects with respect to the sub-attributes.

Linguistic variable	TFN scale
Extreme low (EL)	(0, 1, 2)
Very low (VL)	(1, 2, 3)
Low (L)	(2, 3, 4)
Medium low (ML)	(3, 4, 5)
Medium (M)	(4, 5, 6)
Medium high (MH)	(5, 6, 7)
High (H)	(6, 7, 8)
Very high (VH)	(7, 8, 9)
Extreme high (EH)	(8, 9, 10)

Table 7
Fuzzy dependency and interdependency weights of the selection attributes.

Attribute	S	E	P	O	R	I
Safety (S)	–	–	(0.6, 0.8, 1)	–	–	(1, 1, 1)
System Engineering (E)	(0, 0.2, 0.4)	–	–	(0.2, 0.4, 0.6)	(0.6, 0.8, 1)	(0.6, 0.8, 1)
Program Office (P)	(0.2, 0.4, 0.6)	(0.4, 0.6, 0.8)	–	(0.6, 0.8, 1)	(0.4, 0.6, 0.8)	(1, 1, 1)
Operation (O)	(0.2, 0.4, 0.6)	(0.4, 0.6, 0.8)	(0, 0.2, 0.4)	–	(0, 0.2, 0.4)	(0.4, 0.6, 0.8)
Reliability (R)	–	–	(0.2, 0.4, 0.6)	–	–	(0.6, 0.8, 1)
Implementation (I)	(0, 0.2, 0.4)	–	(0, 0.2, 0.4)	(0.4, 0.6, 0.8)	(0.2, 0.4, 0.6)	–

Table 10
Fuzzy consensus decision matrix.

Attribute	Sub attribute	Project									
		Hubble	Photo-Voltaic	Airlock	Babaloon	Planet-Finder	Nebula	Solar	Truss	Centrifuge	Tether
Safety	ST-DSI	(7, 8, 9)	(5, 6, 7)	(2, 3, 4)	(7, 8, 9)	(1, 2, 3)	(7, 8, 9)	(6, 7, 8)	(5, 6, 7)	(7, 8, 9)	(3, 4, 5)
	ST-LOF	(2, 3, 4)	(6, 7, 8)	(7, 8, 9)	(6, 7, 8)	(5, 6, 7)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(8, 9, 10)	(4, 5, 6)
	ST-PID	(7, 8, 9)	(1, 2, 3)	(5, 6, 7)	(8, 9, 10)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(7, 8, 9)	(8, 9, 10)
	ST-SVS	(6, 7, 8)	(7, 8, 9)	(7, 8, 9)	(1, 2, 3)	(7, 8, 9)	(7, 8, 9)	(5, 6, 7)	(8, 9, 10)	(2, 3, 4)	(4, 5, 6)
	ST-DVS	(5, 6, 7)	(7, 8, 9)	(2, 3, 4)	(3, 4, 5)	(8, 9, 10)	(5, 6, 7)	(8, 9, 10)	(7, 8, 9)	(8, 9, 10)	(1, 2, 3)
Systems Engineering	ET-LSP	(1, 2, 3)	(5, 6, 7)	(0, 1, 2)	(4, 5, 6)	(6, 7, 8)	(4, 5, 6)	(3, 4, 5)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)
	ET-NTR	(6, 7, 8)	(7, 8, 9)	(6, 7, 8)	(4, 5, 6)	(0, 1, 2)	(8, 9, 10)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)
	ET-NON	(2, 3, 4)	(1, 2, 3)	(0, 1, 2)	(3, 4, 5)	(8, 9, 10)	(0, 1, 2)	(3, 4, 5)	(7, 8, 9)	(2, 3, 4)	(2, 3, 4)
	ET-FIX	(6, 7, 8)	(8, 9, 10)	(0, 1, 2)	(7, 8, 9)	(0, 1, 2)	(2, 3, 4)	(7, 8, 9)	(0, 1, 2)	(0, 1, 2)	(7, 8, 9)
	ET-TCH	(1, 2, 3)	(1, 2, 3)	(8, 9, 10)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)
Program Office	PT-PRI	(6, 7, 8)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(6, 7, 8)	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)	(3, 4, 5)
	PT-FUN	(5, 6, 7)	(5, 6, 7)	(7, 8, 9)	(5, 6, 7)	(7, 8, 9)	(5, 6, 7)	(6, 7, 8)	(5, 6, 7)	(7, 8, 9)	(2, 3, 4)
	PT-IMP	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)
	PT-CST	(5, 6, 7)	(6, 7, 8)	(5, 6, 7)	(3, 4, 5)	(6, 7, 8)	(6, 7, 8)	(5, 6, 7)	(2, 3, 4)	(6, 7, 8)	(2, 3, 4)
	PT-SCH	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)	(5, 6, 7)	(4, 5, 6)	(5, 6, 7)	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)
	PT-OMC	(6, 7, 8)	(6, 7, 8)	(5, 6, 7)	(7, 8, 9)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(4, 5, 6)	(5, 6, 7)	(5, 6, 7)
	PT-CON	(6, 7, 8)	(7, 8, 9)	(8, 9, 10)	(7, 8, 9)	(8, 9, 10)	(2, 3, 4)	(8, 9, 10)	(6, 7, 8)	(8, 9, 10)	(7, 8, 9)
Operations	OT-PEP	(2, 3, 4)	(5, 6, 7)	(6, 7, 8)	(1, 2, 3)	(3, 4, 5)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(3, 4, 5)
	OT-TIM	(7, 8, 9)	(8, 9, 10)	(1, 2, 3)	(2, 3, 4)	(5, 6, 7)	(5, 6, 7)	(7, 8, 9)	(3, 4, 5)	(1, 2, 3)	(5, 6, 7)
	OT-LOC	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(1, 2, 3)	(7, 8, 9)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(1, 2, 3)
	OT-HNM	(1, 2, 3)	(3, 4, 5)	(8, 9, 10)	(8, 9, 10)	(1, 2, 3)	(3, 4, 5)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)
Reliability	RT-SFP	(7, 8, 9)	(0, 1, 2)	(7, 8, 9)	(0, 1, 2)	(0, 1, 2)	(7, 8, 9)	(0, 1, 2)	(0, 1, 2)	(6, 7, 8)	(0, 1, 2)
	RT-PFP	(7, 8, 9)	(6, 7, 8)	(0, 1, 2)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(8, 9, 10)	(0, 1, 2)	(1, 2, 3)	(0, 1, 2)
	RT-MTR	(6, 7, 8)	(7, 8, 9)	(6, 7, 8)	(8, 9, 10)	(6, 7, 8)	(5, 6, 7)	(3, 4, 5)	(6, 7, 8)	(5, 6, 7)	(2, 3, 4)
	RT-FII	(6, 7, 8)	(6, 7, 8)	(0, 1, 2)	(7, 8, 9)	(4, 5, 6)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(7, 8, 9)	(0, 1, 2)
	RT-SIM	(7, 8, 9)	(5, 6, 7)	(6, 7, 8)	(0, 1, 2)	(0, 1, 2)	(7, 8, 9)	(5, 6, 7)	(6, 7, 8)	(1, 2, 3)	(6, 7, 8)
	RT-AMT	(5, 6, 7)	(6, 7, 8)	(6, 7, 8)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(7, 8, 9)	(0, 1, 2)	(0, 1, 2)	(5, 6, 7)
	RT-TBF	(6, 7, 8)	(3, 4, 5)	(0, 1, 2)	(0, 1, 2)	(2, 3, 4)	(3, 4, 5)	(5, 6, 7)	(6, 7, 8)	(6, 7, 8)	(7, 8, 9)
	RT-ETT	(0, 1, 2)	(6, 7, 8)	(6, 7, 8)	(8, 9, 10)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(0, 1, 2)	(6, 7, 8)	(6, 7, 8)
	RT-COT	(7, 8, 9)	(1, 2, 3)	(6, 7, 8)	(7, 8, 9)	(4, 5, 6)	(1, 2, 3)	(2, 3, 4)	(7, 8, 9)	(1, 2, 3)	(5, 6, 7)
	RT-EQI	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(7, 8, 9)	(1, 2, 3)	(0, 1, 2)	(7, 8, 9)	(5, 6, 7)	(7, 8, 9)	(0, 1, 2)
PICB	IT-MSA	(0, 1, 2)	(7, 8, 9)	(4, 5, 6)	(7, 8, 9)	(4, 5, 6)	(0, 1, 2)	(7, 8, 9)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)
	IT-WOO	(8, 9, 10)	(7, 8, 9)	(4, 5, 6)	(6, 7, 8)	(3, 4, 5)	(7, 8, 9)	(1, 2, 3)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)
	IT-FMC	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(6, 7, 8)	(3, 4, 5)	(7, 8, 9)	(1, 2, 3)	(7, 8, 9)	(3, 4, 5)	(7, 8, 9)
	IT-MSC	(7, 8, 9)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(7, 8, 9)	(8, 9, 10)	(5, 6, 7)	(5, 6, 7)	(7, 8, 9)	(6, 7, 8)
	IT-EOH	(8, 9, 10)	(4, 5, 6)	(3, 4, 5)	(5, 6, 7)	(4, 5, 6)	(8, 9, 10)	(4, 5, 6)	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)
	IT-SSR	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(6, 7, 8)	(4, 5, 6)	(8, 9, 10)	(2, 3, 4)	(6, 7, 8)	(5, 6, 7)	(5, 6, 7)
	IT-TCH	(0, 1, 2)	(2, 3, 4)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(0, 1, 2)	(0, 1, 2)	(1, 2, 3)	(1, 2, 3)	(3, 4, 5)

six comparison matrices provided by the six DMs. The (–) in this table signifies that there is no dependency between/interdependency among the two attributes while a numerical value shows the degree of relative influence of one attribute on another. Moreover, the reciprocal properties may not be preserved for dependencies and interdependencies.

Next, the weights of the attributes are modified with the fuzzy dependency and interdependency weights given in Table 7 as follows:

$$W_{main\text{-}Criteria} = \begin{bmatrix} W_S \\ W_E \\ W_P \\ W_O \\ W_R \\ W_I \end{bmatrix} = \begin{bmatrix} (0,0,0) & (0,0,0) & (0.6,0.8,1) & (0,0,0) & (0,0,0) & (1,1,1) \\ (0,0.2,0.4) & (0,0,0) & (0,0,0) & (0.2,0.4,0.6) & (0.6,0.8,1) & (0.6,0.8,1) \\ (0.2,0.4,0.6) & (0.4,0.6,0.8) & (0,0,0) & (0.6,0.8,1) & (0.4,0.6,0.8) & (1,1,1) \\ (0.2,0.4,0.6) & (0.4,0.6,0.8) & (0,0.2,0.4) & (0,0,0) & (0,0.2,0.4) & (0.4,0.6,0.8) \\ (0,0,0) & (0,0,0) & (0.2,0.4,0.6) & (0,0,0) & (0,0,0) & (0.6,0.8,1) \\ (0,0.2,0.4) & (0,0,0) & (0,0.2,0.4) & (0.4,0.6,0.8) & (0.2,0.4,0.6) & (0,0,0) \end{bmatrix} \otimes \begin{bmatrix} (0.36,0.38,0.53) \\ (0.03,0.13,0.14) \\ (0.03,0.09,0.11) \\ (0.01,0.06,0.11) \\ (0.06,0.28,0.45) \\ (0.04,0.06,0.07) \end{bmatrix} = \begin{bmatrix} (0.096,0.132,0.24) \\ (0.13,0.372,0.83) \\ (0.194,0.506,1.04) \\ (0.072,0.34,0.848) \\ (0.048,0.084,0.176) \\ (0.048,0.242,0.646) \end{bmatrix}$$

As shown here, the order of importance of the attributes is changed after taking into consideration the dependencies and interdependencies among them. Furthermore, the local fuzzy weights of the sub-attributes were modified using the interdependent weights of their respective attributes. This resulted in achieving a global fuzzy weight for each sub-attribute. The global fuzzy weights of the sub-attributes were calculated by multiplying their local fuzzy weights with the interdependent fuzzy weight of its respective attribute. The resulting global fuzzy weights of the sub-attributes are presented in Table 8.

In the second module, the DMs scored the advanced-technology projects (i.e., the alternatives) with respect to the sub-attributes using the linguistic terms provided in Table 9.

Table 10 presents the fuzzy consensus decision matrix for the six DMs.

The columnar normalization was performed on the data in Table 10. The fuzzy global weights of the sub-attributes, which

Table 11
Fuzzy positive and fuzzy negative distances.

Project	FPD	FND
Hubble	$(-0.063, 0.49, 0.98)$	$(0.402, 0.916, 1.337)$
Photo-Voltaic	$(0.299, 0.818, 1.286)$	$(0.075, 0.554, 0.999)$
Airlock	$(0.04, 0.593, 1.088)$	$(0.299, 0.814, 1.255)$
Babaloon	$(0.364, 0.891, 1.372)$	$(0.001, 0.49, 0.945)$
Planet-Finder	$(0.417, 0.958, 1.423)$	$(-0.065, 0.437, 0.908)$
Nebula	$(0.217, 0.745, 1.235)$	$(0.147, 0.636, 1.091)$
Solar	$(0.407, 0.921, 1.337)$	$(-0.029, 0.447, 0.872)$
Truss	$(-0.04, 0.522, 1.019)$	$(0.371, 0.894, 1.34)$
Centrifuge	$(-0.037, 0.494, 0.967)$	$(0.398, 0.89, 1.31)$
Tether	$(0.045, 0.675, 0.967)$	$(0.451, 0.76, 1.54)$

Table 12
Fuzzy closeness coefficients.

Project	FCC
Hubble	$(0.379, 1.01, 4.242)$
Photo-Voltaic	$(0.252, 0.743, 3.241)$
Airlock	$(0.337, 0.94, 4.304)$
Babaloon	$(0.222, 0.704, 3.357)$
Planet-Finder	$(0.194, 0.675, 3.377)$
Nebula	$(0.28, 0.804, 3.761)$
Solar	$(0.211, 0.67, 2.57)$
Truss	$(0.365, 1.001, 4.68)$
Centrifuge	$(0.38, 0.977, 3.839)$
Tether	$(0.282, 0.67, 3.248)$

Table 13
Final ranking.

Project	$1/K$-value	K-value	Rank	Cost ($)	Cumulative cost ($)
Truss[a]	0.997	1.003	1	1,347,000	1,347,000
Airlock[a]	0.917	1.091	2	1,515,000	2,862,000
Hubble[a]	0.914	1.094	3	1,778,000	4,640,000
Tether[a]	0.834	1.098	4	961,000	5,601,000
Centrifuge	0.835	1.198	5	1,790,000	7,391,000
Nebula	0.796	1.256	6	1,348,000	8,739,000
Babaloon	0.705	1.418	7	1,949,000	10,688,000
Planet-Finder	0.703	1.422	8	1,266,000	11,954,000
Photo-Voltaic	0.688	1.453	9	1,908,000	13,862,000
Solar	0.549	1.821	10	1,176,000	15,038,000

[a] Projects recommended for funding.

were calculated in the first module, were utilized to compute the weighted normalized decision matrix.

The distances between each alternative project from the fuzzy positive ideal solution and fuzzy negative ideal solution are summarized in Table 11. We call these Fuzzy Positive Distance (FPD) and Fuzzy Negative Distance (FND).

The FPDs and the FNDs given in Table 11 were used in Eq. (15) to derive the FCC given in Table 12.

The FCCs given in Table 12 were then ordered in a non-increasing mode based on the PR measurement. This results in the final ranking of the projects presented in Table 13.

As shown in Table 13, given the $6 million total budget made available by NASA's headquarter to KSC, projects Truss, Airlock, Hubble, and Tether with a total cost of $5,601,000 were recommended to the KSC management for funding.

5. Conclusions and future research directions

The ongoing economic crisis that has shaken markets around the world along with the failure of several major financial institutions and the bailout of others have put tremendous pressure on government agencies that support technology development. The public is concerned with the spending in these government agencies and is demanding accountability. Since the global economic crisis has begun, NASA funding has dropped steadily. The continuing cost-cutting measures and the increasing number of projects have made evaluating advanced-technology projects at NASA extremely difficult.

In this paper a hybrid fuzzy group decision support framework was proposed to address the need for a transparent, structured and analytical method for assessing and prioritizing the advanced-technology projects at the Kennedy Space Center. We used ANP to represent the complicated structure of the prioritization criteria and alternatives. This formulation led to modeling the dependencies and interdependencies of the attributes and the alternative advances technology projects. We used linguistic terms parameterized through fuzzy sets to represent the uncertainties associated with the qualitative attributes. A fuzzy goal programming model was constructed to find the fuzzy relative importance weight of the attributes. We then used these fuzzy weights in a TOPSIS model and ranked the advanced- technology projects. The proposed framework is: (i) structured and systematic with step-by-step and well-defined procedures; (ii) simple and transparent with a straightforward computation process; (iii) rational and logical with a sound mathematical and theoretical foundation; (iv) supportive and informative with a scalar value that identifies both the best and worst projects simultaneously; (v) visual and graphical with the ability to visualize the performance measures of all projects on a polyhedron; (vi) realistic and practical with the ability to deal with impreciseness and vagueness in real-world technology assessment problems; and (vii) versatility and flexibility with the ability to be applied to other multi-criteria prioritization problems.

As a direction for future research, it is interesting to utilize the proposed framework under intuitionistic fuzzy sets. Also, the practicality of this framework can be further enhanced through developing the proposed framework into a decision support system to reduce the computation time and effort. Another future research direction, which could be an area of theoretical study, is investigating the similarities and differences between the hybrid method proposed in this study and other MCDM methods. Finally, systematic investigation for different types of weighting, defuzzification and ranking techniques can be carried out to see the effects on the final ranking of the advanced technology projects.

Acknowledgement

This research was supported in part by NASA grants NGT-52605 and NGT-60002.

References

Araúzo, J. A., Pajares, J., & Lopez-Paredes, A. (2010). Simulating the dynamic scheduling of project portfolios. *Simulation Modelling Practice and Theory, 18*(10), 1428–1441.
Awasthi, A., Chauhan, S. S., & Omrani, H. (2011). Application of fuzzy TOPSIS in evaluating sustainable transportation systems. *Expert Systems with Applications, 38*(10), 12270–12280.
Babaesmailli, M., Arbabshirani, B., & Golmah, V. (2012). Integrating analytical network process and fuzzy logic to prioritize the strategies – a case study for tile manufacturing firm. *Expert Systems with Applications, 39*(1), 925–935.
Beaujon, G. J., Marin, S. P., & McDonald, G. C. (2001). Balancing and optimizing a portfolio of R&D projects. *Naval Research Logistics, 48*(1), 18–40.
Bellman, R., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science, 17B*, 141–164.
Boender, C. G. E., de Graan, J. G., & Lootsma, F. A. (1989). Multi-criteria decision analysis with fuzzy pairwise comparisons. *Fuzzy Sets and Systems, 29*(2), 133–143.
Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*(3), 233–247.

Buckley, J. J., Feuring, T., & Hayashi, Y. (2001). Fuzzy hierarchical analysis revisited. *European Journal of Operational Research, 129*, 48–64.

Büyüközkan, G., Çifçi, G., & Güleryüz, S. (2011). Strategic analysis of healthcare service quality using fuzzy AHP methodology. *Expert Systems with Applications, 38*(8), 9407–9424.

Büyüközkam, G., & Feyzioglu, O. (2004). A fuzzy-logic-based decision-making approach for new product development. *International Journal of Production Economics, 90*, 27–45.

Cavallaro, F. (2010). Fuzzy TOPSIS approach for assessing thermal-energy storage in concentrated solar power (CSP) systems. *Applied Energy, 87*(2), 496–503.

Cebeci, U. (2009). Fuzzy AHP-based decision support system for selecting ERP systems in textile industry by using balanced scorecard. *Expert Systems with Applications, 36*, 8900–8909.

Chakraborty, C., & Chakraborty, D. (2007). A theoretical development on a fuzzy distance measure for fuzzy numbers. *Mathematical and Computer Modelling, 43*, 254–261.

Chamodrakas, I., & Martakos, D. (2012). A utility-based fuzzy TOPSIS method for energy efficient network selection in heterogeneous wireless networks. *Applied Soft Computing, 12*(7), 1929–1938.

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research, 95*(3), 649–655.

Chen, S. J., Hwang, C. L., & Hwang, F. P. (1992). *Fuzzy multiple attribute decision making methods and applications*. New York: Springer.

Chen, J., & Yang, Y. (2011). A fuzzy ANP-based approach to evaluate region agricultural drought risk. *Procedia Engineering, 23*, 822–827.

Coldrick, S., Longhurst, P., Ivey, P. C., & Hannis, J. (2005). An R&D options selection model for investment decisions. *Technovation, 25*(3), 185–193.

Csutora, R., & Buckley, J. J. (2001). Fuzzy hierarchical analysis: the lambda-max method. *Fuzzy Sets and Systems, 120*, 181–195.

Dağdeviren, M., Yavuz, S., & Kilinç, N. (2009). Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Systems with Applications, 36*, 8143–8151.

Dağdeviren, M., & Yüksel, I. (2008). Developing a fuzzy analytic hierarchy process (AHP) model for behavior-based safety management. *Information Sciences, 178*, 1717–1733.

Dağdeviren, M., Yüksel, İ, & Kurt, M. (2008). A fuzzy analytic network process (ANP) model to identify faulty behavior risk (FBR) in work system. *Safety Science, 46*(5), 771–783.

Dağdeviren, M., & Yüksel, I. (2010). Using the fuzzy analytic network process (ANP) for balanced scorecard (BSC): a case study for a manufacturing firm. *Expert Systems with Applications, 37*, 1270–1278.

DePiante, A., & Jensen, A. (1999). A practical R&D project-selection scoring tool. *IEEE Transactions on Engineering Management, 46*(2), 158–170.

Dickinson, M. W., Thornton, A. C., & Graves, S. (2001). Technology portfolio management: optimizing interdependent projects over multiple time periods. *IEEE Transactions on Engineering Management, 48*(4), 518–527.

Dyer, R. F., & Forman, E. H. (1992). Group decision support with the analytic hierarchy process. *Decision Support Systems, 8*(2), 99–124.

Ehrgott, M., & Wiecek, M. M. (2005). Multiobjective programming. In J. Figueira, S. Greco, & M. Ehrgott (Eds.), *Multiple criteria decision analysis: state of the art surveys* (pp. 667–722). Springer Science + Business Media, Inc..

Elazouni, A., & Abido, M. (2011). Multiobjective evolutionary finance-based scheduling: Individual projects within a portfolio. *Automation in Construction, 20*(7), 755–766.

Eilat, H., Golany, B., & Shtub, A. (2006). Constructing and evaluating balanced portfolios of R&D projects with interactions: a DEA based methodology. *European Journal of Operational Research, 172*(3), 1018–1039.

Ertugrul, İ., & Karakasoglu, N. (2007). Performance evaluation of Turkish cement firms with fuzzy analytic hierarchy process and TOPSIS methods. *Expert Systems with Applications, 36*(1), 702–715.

Guha, D., & Chakraborty, D. (2010). A new approach to fuzzy distance measure and similarity measure between two generalized fuzzy numbers. *Applied Soft Computing, 10*, 90–99.

Gumus, A. T., & Yilmaz, G. (2010). Sea vessel type selection via an integrated VAHP–ANP methodology for high-speed public transportation in Bosphorus. *Expert Systems with Applications, 37*(6), 4182–4189.

Guneri, A. F., Cengiz, M., & Seker, S. (2009). A fuzzy ANP approach to shipyard location selection. *Expert Systems with Applications, 36*(4), 7992–7999.

Güngör, Z., Serhadlioğlu, G., & Kesen, E. (2009). A fuzzy AHP approach to personnel selection problem. *Applied Soft Computing, 9*, 641–646.

Henriksen, A. D., & Traynor, A. J. (1999). A practical R&D project-selection scoring tool. *IEEE Transactions on Engineering Management, 46*, 158–170.

Ho, S. H., & Liao, S. H. (2011). A fuzzy real option approach for investment project valuation. *Expert Systems with Applications, 38*(12), 15296–15302.

Huang, C. C., Chu, P. Y., & Chiang, Y. H. (2008). A fuzzy AHP application in government-sponsored R&D project selection. *Omega, 36*(6), 1038–1052.

Huang, L.-C., & Wu, R. (2005). Applying fuzzy analytic hierarchy process in the managerial talent assessment model – an empirical study in Taiwan's semiconductor industry. *International Journal of Technology Management, 30*, 105–130.

Hwang, C. L., & Masud, A. S. (1979). *Multiple objective decision making, methods and applications*. New York: Springer-Verlag.

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: methods and applications*. New York: Springer-Verlag.

İç, Y. T. (2012). Development of a credit limit allocation model for banks using an integrated Fuzzy TOPSIS and linear programming. *Expert Systems with Applications, 39*(5), 5309–5316.

Kabak, M., Burmaoğlu & Kazançoğlu, Y. (2012). A fuzzy hybrid MCDM approach for professional selection. *Expert Systems with Applications, 39*(3), 3516–3525.

Kahraman, C., Ertay, T., & Büyüközkan, G. (2006). A fuzzy optimization model for QFD planning process using analytic network approach. *European Journal of Operational Research, 171*, 390–411.

Kaya, T., & Kahraman, C. (2011). Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. *Expert Systems with Applications, 38*(6), 6577–6585.

Keeney, R. L. (1980). *Siting energy facilities*. New York: Academic Press.

Kelemenis, A., Ergazakis, K., & Askounis, D. (2011). Support managers' selection using an extension of fuzzy TOPSIS. *Expert Systems with Applications, 38*(3), 2774–2782.

Kengpol, A., & Tuominen, M. (2006). A framework for group decision support systems: an application in the evaluation of information technology for logistics firms. *International Journal of Production Economics, 101*(1), 159–171.

Kester, L., Hultink, E. J., & Lauche, K. (2009). Portfolio decision-making genres: a case study. *Journal of Engineering and Technology Management, 26*, 327–341.

Kim, S., Lee, K., Cho, J. K., & Kim, C. O. (2011). Agent-based diffusion model for an automobile market with fuzzy TOPSIS-based product adoption process. *Expert Systems with Applications, 38*(6), 7270–7276.

Kong, F., & Liu, H. (2005). Applying fuzzy analytic hierarchy process to evaluate success factors of ecommerce. *International Journal of Information and Systems sciences, 1*(3-4), 406–412.

Krohling, R. A., & Campanharo, V. C. (2011). Fuzzy TOPSIS for group decision making: a case study for accidents with oil spill in the sea. *Expert Systems with Applications, 38*(4), 4190–4197.

Lin, H.-F., Lee, H.-S., & Wang, D. W. (2009). Evaluation of factors influencing knowledge sharing based on a fuzzy AHP approach. *Journal of Information Science, 35*, 25–44.

Linton, J. D., Walsh, S. T., & Morabito, J. (2002). Analysis, ranking and selection of R&D projects in a portfolio. *R and D Management, 32*(2), 139–148.

Meade, L. M., & Sarkis, J. (1999). Analyzing organizational project alternatives for agile manufacturing processes: an analytical network approach. *International Journal of Production Research, 37*, 241–261.

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgements. *Fuzzy Sets and Systems, 134*(3), 365–385.

Mikhailov, L., & Tsvetinov, P. (2004). Evaluation of services using a fuzzy analytic hierarchy process. *Applied Soft Computing, 5*, 23–33.

Modarres, M., & Sadi-Nezhad, S. (2001). Ranking fuzzy numbers by preference ratio. *Fuzzy Set and Systems, 118*, 429–436.

Mokhtarian, M. N., & Hadi-Vencheh, A. (2012). A new fuzzy TOPSIS method based on left and right scores: an application for determining an industrial zone for dairy products factory. *Applied Soft Computing, 12*(8), 2496–2505.

NASA ESAS Final Report. (2005). Section 9.0 Technology Assessment. <http://images.spaceref.com/news/2005/ESAS.REPORT.09.PDF>.

Oh, J., Yang, J., & Lee, S. (2012). Managing uncertainty to improve decision-making in NPD portfolio management with a fuzzy expert system. *Expert Systems with Applications, 39*(10), 9868–9885.

Omkarprasad, S. V., & Sushil, K. (2006). Analytic hierarchy process: an overview of applications. *European Journal of Operational Research, 169*, 1–29.

Onut, S., Tuzkaya, U. R., & Torun, E. (2011). Selecting container port via a fuzzy ANP-based approach: a case study in the Marmara Region, Turkey. *Transport Policy, 18*(1), 182–193.

Paxkan, C., & Wu, M. L. (1997). On the equivalence of operational performance measurement and multiple attribute decision making. *International Journal of Production Research, 35*(11), 2963–2988.

Rajput, H. C., Milani, A. S., & Labun, A. (2011). Including time dependency and ANOVA in decision-making using the revised fuzzy AHP: a case study on wafer fabrication process selection. *Applied Soft Computing, 11*(8), 5099–5109.

Rouhani, S., Ghazanfari, M., & Jafari, M. (2012). Evaluation model of business intelligence for enterprise systems using fuzzy TOPSIS. *Expert Systems with Applications, 39*(3), 3764–3771.

Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology, 15*, 234–281.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Saaty, T. L. (1996). *Decision making with dependence and feedback: the analytic network process*. Pittsburgh: RWS Publications.

Saaty, T. L. (2005). *Theory and applications of the analytic network process*. Pittsburgh: RWS Publications.

Sadi-Nezhad, S., & Khalili-Damghani, K. (2010). Application of a fuzzy TOPSIS method base on modified preference ratio and fuzzy distance measurement in assessment of traffic police centers performance. *Applied Soft Computing, 10*, 1028–1039.

Sadi-Nezhad, S., & Khalili-Damghani, K. (2011). A modified TOPSIS technique in presence of uncertainty and its application to assessment of transportation systems. *International Journal of Management Science and Engineering Management, 6*, 3–13.

Sakawa, M. (1993). *Fuzzy sets and interactive multi-objective optimization*. New York: Plenum Press.

Saremi, M., Mousavi, S. F., & Sanayei, A. (2009). TQM consultant selection in SMEs with TOPSIS under fuzzy environment. *Expert Systems with Applications, 36*(2), 742–2749.

Şen, C. G., & Çinar, G. (2010). Evaluation and pre-allocation of operators with multiple skills: a combined fuzzy AHP and max-min approach. *Expert Systems with Applications, 37*, 2043–2053.
Sevkli, M., Oztekin, A., Uysal, O., Torlak, G., Turkyilmaz, A., & Delen, D. (2012). Development of a fuzzy ANP based SWOT analysis for the airline industry in Turkey. *Expert Systems with Applications, 39*(1), 14–24.
Seyhan, S., & Mehpare, T. (2010). The analytic hierarchy process and analytic network process: an overview of applications. *Management Decision, 48*, 775–808.
Shehabuddeen, N., Probert, D., & Phaal, R. (2006). From theory to practice: challenges in operationalising a technology selection framework. *Technovation, 26*(3), 324–335.
Shih, H. S., Shyur, H. J., & Lee, E. S. (2007). An extension of TOPSIS for group decision making. *Mathematical and Computer Modelling, 45*(7–8), 801–813.
Shyur, H.-J. (2006). COTS evaluation using modified TOPSIS and ANP. *Applied Mathematics and Computation, 177*, 251–259.
Soltanmohammadi, H., Osanloo, M., & Aghajani Bazzazi, A. (2010). An analytical approach with a reliable logic and a ranking policy for post-mining land-use determination. *Land Use Policy, 27*(2), 364–372.
Sredjevic, B., & Medeiros, Y. D. P. (2008). Fuzzy AHP assessment of water management plans. *Water Resources Management, 22*, 877–894.
Stamelos, I., & Angelis, L. (2001). Managing uncertainty in project portfolio cost estimation. *Information and Software Technology, 43*(13), 759–768.
Sun, H., & Ma, T. (2005). A packing-multiple-boxes model for R&D project selection and scheduling. *Technovation, 25*(11), 1355–1361.
Tavana, M. (2003). CROSS: a multi-criteria group-decision-making model for evaluating and prioritizing advanced-technology projects at NASA. *Interfaces, 33*, 40–56.
Tiryaki, F., & Ahlatcioglu, B. (2009). Fuzzy portfolio selection using fuzzy analytic hierarchy process. *Information Sciences, 179*(1–2), 53–69.
Tolga, E., Demircan, M. L., & Kahraman, C. (2005). Operating system selection using fuzzy replacement analysis and analytic hierarchy process. *International Journal of Production Economics, 97*, 89–117.
Torlak, G., Sevkli, M., Sanal, M., & Zaim, S. (2011). Analyzing business competition by using fuzzy TOPSIS method: an example of Turkish domestic airline industry. *Expert Systems with Applications, 38*(4), 3396–3406.
Triantaphyllou, E., & Lin, C. T. (1996). Development and evaluation of five fuzzy multiattribute decision making methods. *International Journal of Approximate Reasoning, 14*, 281–310.
Tuzkaya, U. R., & Önüt, S. (2008). A fuzzy analytic network process based approach to transportation-mode selection between Turkey and Germany: a case study. *Information Sciences, 178*(15), 3133–3146.
Vithayasrichareon, P., & MacGill, I. F. (2012). A Monte Carlo based decision-support tool for assessing generation portfolios in future carbon constrained electricity industries. *Energy Policy, 41*, 374–392.
Wang, Y. J. (2008). Applying FMCDM to evaluate financial performance of domestic airlines in Taiwan. *Expert Systems with Applications, 34*(3), 1837–1845.
Wang, X., Chan, H. K., Yee, R. W. Y., & Diaz-Rainey, I. (2012). A two-stage fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.
Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. *Expert Systems with Applications, 31*, 309–319.
Wang, Y. M., Yang, J. B., & Xu, D. L. (2005). A two-stage logarithmic goal programming method for generating weights from interval comparison matrices. *Fuzzy Sets Systems, 152*, 475–498.
Xu, R. (2000). Fuzzy least square priority method in the analytic hierarchy process. *Fuzzy Sets and Systems, 112*(3), 395–404.
Yeh, D., & Yo-Hern, Ch. (2000). Fuzzy multi criteria analysis for performance evaluation of bus companies. *European Journal of Operational Research, 126*, 459–473.
Zanakis, S. H., Solomon, A., Wishart, N., & Dublish, S. (1998). Multi-attribute decision making: a simulation comparison of select methods. *European Journal of Operational Research, 107*, 507–529.
Zapata, J. C., & Reklaitis, J. V. (2010). Valuation of project portfolios: an endogenously discounted method. *European Journal of Operational Research, 206*(3), 653–666.
Zimmermann, H.-J. (1985). *Fuzzy set theory and its applications*. Dordrecht, Boston: Kluwer Academic Publishers.