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Full Length Research Paper

Fuzzy multi-criteria decision making method for facility location selection

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Facility location selection is a multi-criteria decision problem and has a strategic importance for many companies. The aim of this study is to propose a fuzzy approach for facility location selection. This paper is based on a fuzzy extension of the technique for order preference by similarity to ideal solution (TOPSIS) method. In this method, the ratings of various alternatives versus various subjective criteria and the weights of all criteria are assessed in linguistic variables represented by fuzzy numbers. Fuzzy numbers try to resolve the ambiguity of concepts that are associated with human being's judgments. To determine the order of the alternatives, closeness coefficient is defined by calculating the distances to the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS). By using fuzzy TOPSIS, uncertainty and vagueness from subjective perception and the experiences of decision maker can be effectively represented and reached to a more effective decision.

Key words: Fuzzy logic, multi-criteria decision making, fuzzy technique for order preference by similarity to ideal solution (TOPSIS), facility location selection.

INTRODUCTION

Facility location selection is the determination of a geographic site for a firm's operations. The facility location decision involves organizations seeking to locate, relocate or expand their operations. The facility location decision process encompasses the identification, analysis, evaluation and selection among alternatives (Yang and Lee, 1997). Selecting a plant location is a very important decision for firms because they are costly and difficult to reverse, and they entail a long term commitment. And also location decisions have an impact on operating costs and revenues. For instance, a poor choice of location might result in excessive transportation costs, a shortage of qualified labor, lost of competitive advantage, inadequate supplies of raw materials, or some similar condition that would be detrimental to operations (Stevenson, 1993). The conventional approaches for facility location problems like locational cost volume analysis, factor rating, and center of gravity method (Stevenson, 1993) tend to be less effective in dealing with the imprecise or vague nature of the linguistic assessment (Kahraman et al., 2003). In real life, the evaluation data of plant location suitability for various subjective criteria and the weights of the criteria are usually expressed in linguistic terms. And also, to efficiently resolve the ambiguity frequently arising in available information and do more justice to the essential fuzziness in human judgment and preference, the fuzzy set theory has been used to establish an ill defined multiple criteria decision-making problems (Liang, 1999). Thus in this paper, fuzzy TOPSIS method is proposed for facility location selection, where the ratings of various alternative locations under various subjective criteria and the weights of all criteria are represented by fuzzy numbers.

FUZZY SETS AND FUZZY NUMBERS

Fuzzy set theory, which was introduced by Zadeh (1965)

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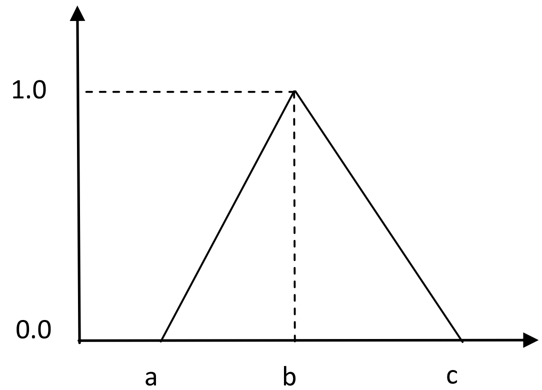

Figure 1. A triangular fuzzy number $\tilde{A}$.

to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework. A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(X)$, which assigns each element x in the universe of discourse X a real number in the interval [0,1]. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a, b, c) as illustrated in Figure 1. The membership function $\mu_{\tilde{A}}(X)$ is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & a \le x \le b \\ \frac{x-c}{b-c} & b \le x \le c \\ 0 & oterwise \end{cases} \quad (1)$$

Basic arithmetic operations on triangular fuzzy numbers $A_1 = (a_1, b_1, c_1)$, where $a_1 \le b_1 \le c_1$, and $A_2 = (a_2, b_2, c_2)$, where $a_2 \le b_2 \le c_2$, can be shown as follows:

addition:

$$A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (2)$$

subtraction:

$$A_1 \ominus A_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \quad (3)$$

Multiplication: if K is a scalar:

$$k \otimes A_1 = \begin{cases} (ka_1, kb_1, kc_1), & k > 0 \\ (kc_1, kb_1, ka_1), & k < 0 \end{cases}$$

$$A_1 \otimes A_2 \approx (a_1a_2, b_1b_2, c_1c_2),$$

$$\text{if } a_1 \ge 0, a_2 \ge 0 \quad (4)$$

$$\text{Division: } A1 \oslash A2 \approx \left(\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}\right),$$

$$\text{if } a_1 \ge 0, a_2 \ge 0 \quad (5)$$

Although multiplication and division operations on triangular fuzzy numbers do not necessarily yield a triangular fuzzy number, triangular fuzzy number approximations can be used for many practical applications (Kaufmann and Gupta, 1988). Triangular fuzzy numbers are appropriate for quantifying the vague information about most decision problems including Facility location selection. The primary reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation (Karsak, 2002). A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill defined to be described in conventional quantitative terms (Zadeh, 1975).

THE FUZZY TOPSIS METHOD

This study uses this method to select facility location. 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 and 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 discuss extends the TOPSIS to the fuzzy environment (Yan and 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 et al. (2008) is as described thus.

Step 1: Determine the weighting of evaluation criteria

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

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

$$\tilde{D} = \begin{matrix} & C_1 & C_2 & \cdots & C_N \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{matrix} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}$$

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \ldots + \tilde{x}_{ij}^k) \quad (6)$$

Table 1. Linguistic scales for the importance of each criterion.

Linguistic variable	Corresponding triangular fuzzy number
Very low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very high (VH)	(0.7, 0.9, 1.0)

Where $\tilde{x}_{ij}^{k}$ is the rating of alternative A_i with respect to criterion C_j evaluated by K 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 $\tilde{R}$ is shown as following formula:

$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$,i=1,2,…,m; j =1,2,…,n (7)

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 $\tilde{r}_{ij}$ 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 $\tilde{V}$:

$\tilde{v} = [\tilde{v}_{ij}]_{m\times n}$, I = 1,2,…,m; j =1,2,…,n (8)

$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$ (9)

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 $\tilde{V}_{ij}$ 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 the following formula:

$A^{+} = (\tilde{V}_1^{+}, \tilde{V}_2^{+}, \ldots, \tilde{V}_n^{+})$ (10)

$A^{-} = (\tilde{V}_1^{-}, \tilde{V}_2^{-}, \ldots, \tilde{V}_n^{-})$ (11)

where $\tilde{V}_j^{+}$ =(1,1,1) and $\tilde{V}_j^{-}$=(0,0,0) j=1,2,…,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.

$d_i^{+} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^{+})$,
i = 1,2,…,m;j = 1,2,…,n (12)

$d_i^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^{-})$,
i = 1,2,…,m;j = 1,2,…,n (13)

Step 6: Obtain the closeness coefficient (CC) 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. Calculate similarities to ideal solution. This step solves the similarities to an ideal solution by formula:

$CC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}$ i =1,2,…,m (14)

According to the CCi, 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 et al. (2008) adopted fuzzy TOPSIS for order selection and pricing of manufacturer (supplier) with make-to-order basis when orders exceed production capacity. Chen et al. (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 et al. (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 et al. (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 Lee (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 et al. (2007) proposed a fuzzy hierarchical TOPSIS model for the multi-criteria evaluation of the industrial robotic systems. Benı´tez et al. (2007) presented a fuzzy TOPSIS approach for evaluating dynamically the service quality of three hotels of an important corporation in Gran Canaria Island via

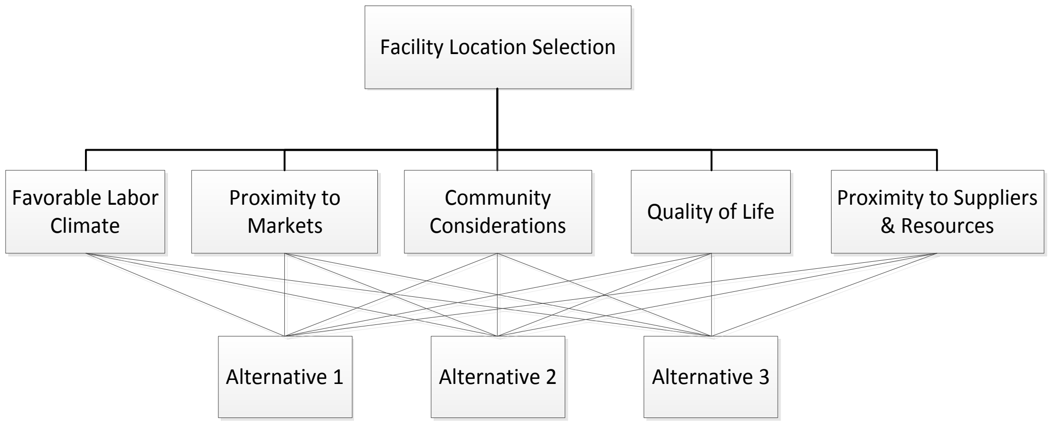

Figure 2. Hierarchical structure of facility location selection process.

surveys. Wang and Elhang (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.

APPLICATION OF FUZZY TOPSIS APPROACH

Our application is related with the facility location problem of an integrated Electerofan Company. This company experienced a growth in the demand for its products and has also unsatisfied from the expansion of existing location. Company desires to find a new location and it has three alternatives (A_1, A_2, A_3). First of all, a committee of decision-makers is formed. Similarly to Ertuğrul et al (2008), criteria are determined as favorable labor climate (C_1), proximity to markets (C_2), community considerations (C_3), quality of life (C_4), proximity to suppliers and resources (C_5). The hierarchical structure for the selection of the best facility location is as seen in Figure 2.

After the construction of the hierarchy the different priority weights of each criteria, attributes and alternatives are calculated using the fuzzy TOPSIS approach. The comparison of the importance or preference of one criterion, attribute or alternative over another can be done with the help of the questionnaire. The method of calculating priority weights of the different decision alternatives is further discussed.

Step 1: Determine the linguistic weighting of each criteria

We adopt fuzzy TOPSIS method to evaluate the weights of different criteria for selecting Facility location. Following the construction of fuzzy TOPSIS model, it is extremely important that experts fill the judgment matrix. From the viewpoint of expert validity, the buildup of most of the operationalizations was based on the literature that caused them to have expert validity. The result of the fuzzy decision reached by each alternative is a fuzzy number and the average fuzzy numbers is shown in the second column in Table 2. Therefore, it is necessary that a non fuzzy ranking method for fuzzy numbers be employed for comparison of each alternative. In other words, the procedure of defuzzification is to locate the Best Non fuzzy Performance value (BNP). Methods of such defuzzified fuzzy ranking generally include mean of maximal (MOM), center of area (COA), and a-cut. The COA method to find out the BNP is a simple and practical method, so it is used in this study.

To take the BNP value of the weight of C_1 as an example, the calculation process is as follows:

$$BNP_{w_1} = [(U_{w_1} - L_{w_1}) + (M_{w_1} - L_{w_1})]/3 + L_{w_1} = [(0.94-0.58)+(0.78-0.58)]/3+0.58=0.77 \quad (15)$$

Then, the weights for the remaining dimensions can be found as shown in Table 2. Table 2 shows the relative weight of criteria, which obtained by fuzzy TOPSIS method. The weights for each criterion are: C_1 (0.77), C_2 (0.72), C_3 (0.71), C_4 (0.78) and C_5 (0.60). From the fuzzy TOPSIS results, we can understand the first two important factors for selecting facility location are C_4 (0.78) and C_1 (0.77). Moreover, the less important factor is C_5 (0.60).

Step 2: Estimating the performance

This paper focuses on determining facility location; so, we assume that questionnaire have collected completely and will start with building dataset that are collected. The evaluators have their own range for the linguistic variables employed in this study according to their subjective judgments (Hsieh et al., 2004). For each evaluator with the same importance; this study employs judgment values of different evaluators regarding the

Table 2. Weights of each criterion.

Criterion	Fuzzy number	BNP	Rank
C_1	(0.58, 0.78, 0.94)	0.77	2
C_2	(0.55, 0.75, 0.85)	0.72	3
C_3	(0.53, 0.73, 0.88)	0.71	4
C_4	(0.60, 0.80, 0.94)	0.78	1
C_5	(0.40, 0.60, 0.79)	0.60	5

Table 3. Linguistic scales for the rating of each cluster policy.

Linguistic variable	Corresponding triangular fuzzy number
Very poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very good (VG)	(7, 9, 10)

Table 4. Subjective cognition results of evaluators towards the five levels of linguistic variables.

	A_1	A_2	A_3
C_1	(4.67, 6.67, 8.42)	(3.50, 5.33, 7.33)	(2.50, 4.33, 6.33)
C_2	(3.5, 5.33, 7.33)	(2.50, 4.33, 6.33)	(2.08, 4.00, 6.00)
C_3	(4.83, 6.83, 8.67)	(4.67, 6.67, 8.58)	(3.83, 5.83, 7.83)
C_4	(4.00, 6.00, 8.00)	(3.17, 5.17, 7.17)	(2.45, 4.45, 6.45)
C_5	(5.17, 7.17, 9.00)	(4.67, 6.67, 8.50)	(3.50, 5.50, 7.50)

Table 5. Normalized fuzzy decision matrix.

	A_1	A_2	A_3
C_1	(0.52, 0.74, 0.94)	(0.39, 0.59, 0.81)	(0.28, 0.48, 0.70)
C_2	(0.39, 0.59, 0.81)	(0.28, 0.48, 0.70)	(0.23, 0.44, 0.67)
C_3	(0.54, 0.76, 0.96)	(0.52, 0.74, 0.95)	(0.43, 0.65, 0.87)
C_4	(0.44, 0.67, 0.89)	(0.35, 0.57, 0.80)	(0.27, 0.49, 0.72)
C_5	(0.57, 0.80, 1.00)	(0.52, 0.74, 0.94)	(0.39, 0.61, 0.83)

same evaluation dimensions. The evaluators then adopted linguistic terms (Table 3), including “very poor”, “poor”, “fair”, “good” and “very good” to express their opinions about the rating of every person, based on the fuzzy data of the four person listed in Table 4.

Step 3: Normalize the fuzzy decision matrix

Using Equation 7, we can normalize the fuzzy decision matrix as Table 5.

Step 4: Establish the weighted normalized fuzzy decision matrix

The forth step in the analysis is to find the weighted fuzzy decision matrix, and the resulting fuzzy weighted decision matrix is as shown in Table 6. The lower bound of C_1 for A_1 in Table 6 is equal to the lower bound of C_1 for A_1 in Table 5 multiplied by lower bound of C_1 in Table 2.

Step 5: 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^+andA^-. This is the fifth step of the fuzzy TOPSIS analysis.

Step 6: Ranking the alternatives

In order to calculate the closeness coefficients of each of the alternatives d_i^+ and d_i^- calculation is used as an

Table 6. Weighted normalized fuzzy decision matrix.

	A_1	A_2	A_3
C_1	(0.11, 0.16, 0.20)	(0.08, 0.13, 0.17)	(0.06, 0.10, 0.15)
C_2	(0.08, 0.12, 0.16)	(0.06, 0.10, 0.14)	(0.05, 0.09, 0.13)
C_3	(0.11, 0.15, 0.19)	(0.10, 0.15, 0.19)	(0.08, 0.13, 0.17)
C_4	(0.10, 0.15, 0.19)	(0.08, 0.13, 0.17)	(0.06, 0.11, 0.16)
C_5	(0.10, 0.13, 0.17)	(0.09, 0.12, 0.16)	(0.06, 0.10, 0.14)

Table 7. Closeness coefficients and ranking.

	d_i^+	d_i^-	CC_i	Rank
A_1	4.33	0.70	0.14	1
A_2	4.38	0.65	0.13	2
A_3	4.41	0.63	0.12	3

example as follows.Once the distances of cluster policy from FPIS and FNIS are determined, the closeness coefficient can be obtained with Equation 14. The index CC_1 of first alternative is calculated as:

$d_i^+ = 4.33 \qquad d_i^- = 0.70$

From the alternative evaluation results in Table 7, the best location is the firstalternative (A_1).

$$CC_1 = \frac{0.70}{4.33+0.70} = 0.14$$

$$CC_1 > CC_2 > CC_3$$

Conclusion

Decision-making process is getting harder in today's complex environment. Decision makers face up to the uncertainty and vagueness from subjective perceptions and experiences in the decision-making process. Multi-criteria decision systems need experts in different areas. Fuzzy decision making theory can be used in many decision making areas like that. The aim of this study is to propose fuzzy TOPSIS approach for selecting facility location. Favorable labor climate, proximity to markets, community considerations, quality of life and proximity to suppliers and resources factors were evaluated to obtain the preference degree associated with each alternative for selecting the most appropriate one. By the help of the fuzzy approach, the ambiguities involved in the assessment data could be effectively represented and processed to make a more effective decision. As a result of the fuzzy TOPSIS method, Alternative 1 is the best location as its closeness coefficient is the highest.

REFERENCES

Abo-Sinna MA, Amer AH, Ibrahim AS (2008). Extensions of TOPSIS for large scale multi-objective non-linear programming problems with block angular structure. Appl. Math. Modelling, 32(3): 292–302.

Ashtiani B, Haghighirad F, Makui A, Montazer GA (2008). Extension of fuzzy TOPSIS method based on interval-valued fuzzy sets. Appl. Soft Comput. doi:10.1016/j.asoc.2008.05.005.

Benı´ tez JM, Martı´n JC, Roman C (2007). Using fuzzy number for measuring quality of service in the hotel industry. Tour. Manage., 28(2): 544–555.

Buyukozkan G, Feyziog˘lu O, Nebol E (2007). Selection of the strategic alliance partner in logistics value chain. Int. J. Prod. Econ. 113(1): 148–158.

Chen CT, Lin CT, Huang SF (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. Int. J. Prod. Econ., 102(2): 289–301.

Chen TY, Tsao CY (2008). The interval-valued fuzzy TOPSIS method and experimental analysis. Fuzzy Sets Syst., 159(11): 1410–1428.

Ertuğrul I, Karakaşoğlu N (2008). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. Int. J. Adv. Manuf. Technol., 39:783–795, DOI 10.1007/s00170-007-1249-8.

Hsieh TY, Lu ST, Tzeng GH (2004). Fuzzy MCDM approach for planning and design tenders selection in public office buildings. Int. J. Proj. Manage., 22(7), 573–584.

Kahraman C, Cebeci U, Ulukan Z (2003). Multi-criteria supplier selection using fuzzy AHP. Logist Inform. Manag., 16(6):382–394.

Kahraman C, Cevik S, Ates NY, Gulbay M (2007). Fuzzy multi-criteria evaluation of industrial robotic systems. Comput. Ind. Eng., 52(4): 414–433.

Karsak EE (2002). Distance-based fuzzy MCDM approach for evaluating flexible manufacturing system alternatives. Int. J. Prod. Res., 40(13): 3167–3181.

Kaufmann A, Gupta MM (1988). Fuzzy mathematical models in engineering and management science. Amsterdam: North-Holland.

Li DF (2007). Compromise ratio method for fuzzy multi-attribute group decision making. Appl. Soft Comput., 7(3): 807–817.

Liang GS (1999). Fuzzy MCDM based on ideal and anti-ideal concepts. Eur. J. Oper. Res., 112:682–691.

Lin HT, Chang WL (2008). Order selection and pricing methods using flexible quantity and fuzzy approach for buyer evaluation. Eur. J. Oper. Res., 187(2): 415–428.

Mahdavi I, Mahdavi-Amiri N, Heidarzade A, Nourifar R (2008). Designing a model of fuzzy TOPSIS in multiple criteria decision making. Applied Mathematics and Computation. doi:10.1016/j.amc.2008.05.047.

Stevenson WJ (1993). Production/operations management. 4th edn. Richard D. Irwin Inc., Homewood.
Wang TC, Chang TH (2007). Application of TOPSIS in evaluating initial training aircraft under a fuzzy environment. Expert Syst. Applications, 33: 870–880.
Wang YM, Elhag TMS (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Syst. Appl., 31(2): 309–319.
Wang YJ, Lee HS (2007). Generalizing TOPSIS for fuzzy multiple-criteria group decision-making. Comput. Math. Appl., 53(11): 1762–1772.
Yang J, Lee H (1997). An AHP decision model for facility location selection. Facilities, 15(9/10):241–254.
Yan T, Hung CC (2007). Multiple-attribute decision making methods for plant layout design problem. Robotics and Computer-Integrated Manuf., 23(1): 126–137.
Zadeh LA (1965). Fuzzy sets. Inform. Control, 8(3): 338–353.
Zadeh LA (1975). The concept of a linguistic variable and its application to approximate reasoning-I. Inform. Sci., 8(3):199–249.